

# Deliverable 3.2

Finalised models/simulation environments, methodology factsheets and user support materials

Public Version

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## Document Control Page

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## Project Executive Summary

The EU-funded 'Predictive Approaches for Safer Urban Environment' (PHOEBE) project aims to develop an integrated, dynamic human-centred predictive safety assessment framework in urban areas. This will be achieved by bringing together the interdisciplinary power of traffic simulation, road safety assessment, human behaviour, mode shift and induced demand modelling and new and emerging mobility data.

Focused on vulnerable road users' safety, the 3.5-year-long PHOEBE project will draw inspiration from real-world scenarios in the three pilot cities of Athens (GR), Valencia (ES) and West Midlands (UK). Testing activities will be performed across the use cases to simulate and forecast the impact of changes on safety in different scenarios of disruptions or transitions across urban transport networks.

Predicting and visualising the safety and socioeconomic outcomes of new forms of transport, new technologies, or regulatory and behavioural changes from the individual (micro) level up to the network-wide (macro) level will also be a significant game-changer for urban stakeholders. The results of PHOEBE can be used as a blueprint by other European cities to develop their knowledge products, such as socioeconomic analysis model, urban road safety assessment, human behaviour and choice modelling.

## PHOEBE pilot cities

List of participating cities:

- Athens (Greece)
- Valencia (Spain)
- West Midlands (United Kingdom)

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## Project Partners

| Organisation                                    | Country | Abbreviation |
|-------------------------------------------------|---------|--------------|
| EVROPSKI INSTITUT ZA OCENJEVANJE CEST - EURORAP | SI      | EIRA         |
| ETHNICON METSOVION POLYTECHNION                 | EL      | NTUA         |
| TECHNISCHE UNIVERSITEIT DELFT                   | NL      | TUD          |
| TECHNISCHE UNIVERSITAET MUENCHEN                | DE      | TUM          |
| AIMSUN SLU                                      | ES      | AIM          |
| POLIS AISBL                                     | BE      | POLIS        |
| FACTUAL CONSULTING SL                           | ES      | FC           |
| UNIVERSITAT POLITECNICA DE VALENCIA             | ES      | UPV          |
| OSEVEN SINGLE MEMBER PRIVATE COMPANY            | EL      | O7           |
| THE FLOW LIMITED                                | UK      | FLOW         |
| INTERNATIONAL ROAD ASSESSMENT PROGRAMME         | UK      | iRAP         |

## List of abbreviations and acronyms

| Acronym | Meaning                                                    |
|---------|------------------------------------------------------------|
| AADT    | Average Annual Daily Traffic                               |
| AD      | Anomaly Detection                                          |
| AI      | Artificial intelligence                                    |
| AIC     | Akaike Information Criterion                               |
| API     | Application Programme Interface                            |
| AR      | Autoregressive                                             |
| ATH     | Athens                                                     |
| AWET    | Access-Wait-Egress Time                                    |
| BIC     | Bayesian Information Criterion                             |
| CBA     | Cost-Benefit Analyses                                      |
| CF      | Calibration Factor                                         |
| CI      | Confidence Interval                                        |
| CLMM    | Cumulative Logit Mixed Model                               |
| CODA    | Crossing Outside Designated Areas                          |
| CSV     | Comma-Separated Values                                     |
| CV      | Coefficient of Variance                                    |
| DX.X    | Deliverable X.X                                            |
| EL      | Greece                                                     |
| ES      | Spain                                                      |
| ESS     | EVT Suitability Score                                      |
| EVT     | Extreme Value Theory                                       |
| FSIs    | Fatal and Severe Injuries                                  |
| FHWA    | Federal Highway Administration                             |
| GAMLSS  | Generalized Additive Models for Location, Scale, and Shape |
| GBP     | Great Britain Pound                                        |
| GEV     | Generalized Extreme Value                                  |
| GIS     | Geographical Information System                            |
| GP      | Generalized Pareto                                         |
| ICC     | Intraclass Correlation Coefficient                         |
| ID      | Identification                                             |
| IForest | Isolation Forest                                           |
| KPIs    | Key Performance Indicator                                  |



| Acronym | Meaning                        |
|---------|--------------------------------|
| KS      | Kolmogorov–Smirnov             |
| L       | Lower bound                    |
| MCD     | Minimum Covariance Determinant |
| MCMC    | Markov Chain Monte Carlo       |
| ML      | Machine learning               |
| MNL     | Multinomial Logit Model        |
| N/A     | Not Applicable                 |
| NCBs    | Non-Compliant Behaviours       |
| NUTS    | No U-Turn Sampler              |
| OD      | Origin Destination             |
| P       | Probability                    |
| PET     | Post-Encroachment Time         |
| PT      | Public Transport               |
| ROI     | Region of interest             |
| RDS     | Real data sets                 |
| RLV     | Red-Light Violation            |
| SEA     | Socioeconomic Analysis         |
| SIM     | Simulation                     |
| SM      | Share Mobility                 |
| SP      | Stated preference (survey)     |
| SR      | Star Ratings                   |
| SRS     | Star Rating Score              |
| STD     | Standard                       |
| SVO     | Social value orientation       |
| TAZ     | Traffic Analysis Zone          |
| TTC     | Time to Collision              |
| U       | Upper bound                    |
| UK      | United Kingdom                 |
| V.      | Version                        |
| VAL     | Valencia                       |
| VBA     | Visual Basic                   |
| VKT     | Vehicle-kilometres travelled   |
| VRU     | Vulnerable road users          |
| WM      | West Midlands                  |
| WP      | Work package                   |



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# Deliverable executive summary

This comprehensive report underscores the interdisciplinary and data-driven nature of the PHOEBE project, advancing urban road safety modelling by integrating human factors, dynamic risk assessment, and traffic simulation within a unified framework, validated and demonstrated in diverse European urban contexts.

**Deliverable 3.2** closes Work Package 3 activities within the PHOEBE project, focusing on the development, refinement, and integration of the components in the PHOEBE framework. They are:

- Mode shift and induced demand
- Human behaviour
- Risk assessment
- Traffic simulation

For each component, models were developed or enhanced to estimate the safety impact of changes better and capture human decision-making processes in urban mobility contexts, with a particular emphasis on mode shift, induced demand, and active travel behaviours.

This deliverable document presents the finalised versions of the models developed through iterative technical enhancements and empirical validation across the three PHOEBE use cases: Athens (EL), Valencia (ES), and the West Midlands (UK). Each model was encoded into the Aimsun Next simulation environment and tested using scenario-specific interventions.

The framework's integration involves structured internal data flows, with scripts and APIs developed to process microsimulation outputs (speed, flows, trajectories) into formats suitable for demand, behaviour, and risk models. Aggregation and transformation steps align data resolutions across components. The integration flow is organized into setup, simulation, and refinement stages, facilitating iterative model runs and indicator calculations. User guides and performance indicator definitions support framework operationalization. PHOEBE provides a comprehensive set of Key Performance Indicators (KPIs) across four categories: health and safety, mode shift, environment and operations.

Deliverable 3.2 successfully finalizes and demonstrates the PHOEBE framework's components across pilot cities, showcasing advancements in predictive urban safety assessment with a focus on VRUs. The integration of mode shift, human behaviour, risk assessment, and traffic simulation models provides a robust foundation for evaluating safety impacts of urban interventions. Future work will focus on automation, scalability, user guidance, and stakeholder engagement to facilitate broader adoption across European cities



# Progress beyond the state of the art and play

**Deliverable 3.2** enhances the existing state of the art in several noteworthy ways:

The PHOEBE project merges traffic simulation, road safety evaluation, human behaviour modelling, mode shift analysis, and induced demand modelling with cutting-edge mobility data. This interdisciplinary strategy is distinctive and offers a thorough framework for assessing urban safety. By integrating these elements, it addresses a critical gap in contemporary methodology, as safety analyses have typically been conducted in a fragmented manner. Each element has also been individually improved using advanced modelling techniques, including the development of the crash x conflict relationship, and by utilising emerging data sources such as crowdsourced mobility data and AI/ML-derived features. This method not only bridges significant data gaps but also guarantees the universal applicability of data manipulation techniques. Furthermore, this integration allows decision-makers to more easily evaluate safety performance indicators when simulating urban interventions intended for implementation in European cities.

A crucial aspect of this integrated framework is the establishment of a set of unified safety indicators across all components, ensuring their harmonisation for seamless connections among them—something that, to the best of our knowledge, has never been accomplished before. Special focus is placed on VRUs and new emerging transportation modes (e.g., micro-mobility), areas that remain with elements underexplored in road safety literature. Lastly, the project has introduced dynamic safety indicators that illustrate how road safety risks vary throughout the day. This facilitates detailed safety analyses, enabling decision-makers to pinpoint and address specific issues at various times, resulting in more focused, effective, and innovative interventions.



# 1. Introduction

This document aims to record the achievements of WP3 of the PHOEBE Project. WP3 demonstrates the operationalisation of the integrated, dynamic, human-centred predictive safety assessment framework for urban areas. The document presents the finalised models and methodology descriptions, the simulation environments, and user support materials for the simulation developments, along with the results of the demonstration. The deliverable includes the following key components::

- Mode Shift and Induced Demand Models: These models estimate the safety impact of changes in urban mobility, focusing on mode shift, induced demand, and active travel behaviours.
- Human Behaviour Models: These models incorporate human factors and road user behaviours into traffic microsimulation and road safety assessments.
- Risk Assessment Models: These models evaluate the risk of road infrastructure and provide dynamic safety analysis for routes used by VRUs.
- Traffic Simulation Models: These models simulate traffic conditions and assess the impact of various interventions on urban safety.

The document also details the integration of these components into the PHOEBE framework, the challenges faced during the integration process, and the solutions implemented to overcome them. Additionally, it highlights the progress made beyond the state of the art, such as the development of unified safety indicators and the introduction of dynamic safety indicators 10 11.

**Deliverable 3.2** achieves its objectives by presenting the results framework for the pilot, the technical evaluation of the model enhancements and the final refinements conducted in the individual models for integration. The finalised version of the model is presented in the initial chapter, followed by the completion of the use case demonstrations as the final enhancements produced and delivered in activities 3.1, 3.2, 3.3. and 3.4.

The framework was utilized in three pilot study locations: Athens, Valencia, and the West Midlands. Each case study represents unique urban typologies and policy contexts. The interventions chosen and detailed in **Deliverable 4.1** evolved throughout the project life cycle. They were tailored to align with the framework's demonstration of its capabilities, as well as the political climate and mobility trends in each pilot area. The scenarios utilised for the framework testing encompass a wide range of different changes that can help in cities and have impacts on safety, mobility, and the economy. They include changes like implementation or removal of bicycling infrastructure, an increase in the spaces dedicated to pedestrians, an increase in the market share of e-scooters, and changes in speed limits.

These demonstrations are supported by strong data foundations established in WP2, which include crowdsourced mobility data and features derived from AI/ML, documented in a detailed data feature register found in **Deliverables 2.1 and 2.2**. The results presented in this deliverable will be used in ongoing consultations with stakeholders to support analysis and guide necessary adjustments and refinements.

Please note that **Deliverable 3.2** builds on the PHOEBE project's past achievements... The theoretical framework, designed after a comprehensive literature review and consultation with key stakeholders, serves as the basis for the technical developments in WP3. The description of the theoretical framework is presented in **Deliverable 1.2**.

To operationalise the framework, a series of enhancements and model developments were performed as part of WP3. The establishment of the statistical model use, the upgrades in the AIMSUN Next software, and version 3.10 of the risk assessment model were presented in **Deliverable 3.1**.



Finally, the framework operationalisation that will be demonstrated in the following chapters of **Deliverable 3.2** is based on the testing scenarios agreed with local stakeholders and documented in **Deliverable 4.1**. Figure 1-1 presents the connection of D3.2 with the content presented in the past deliverables.

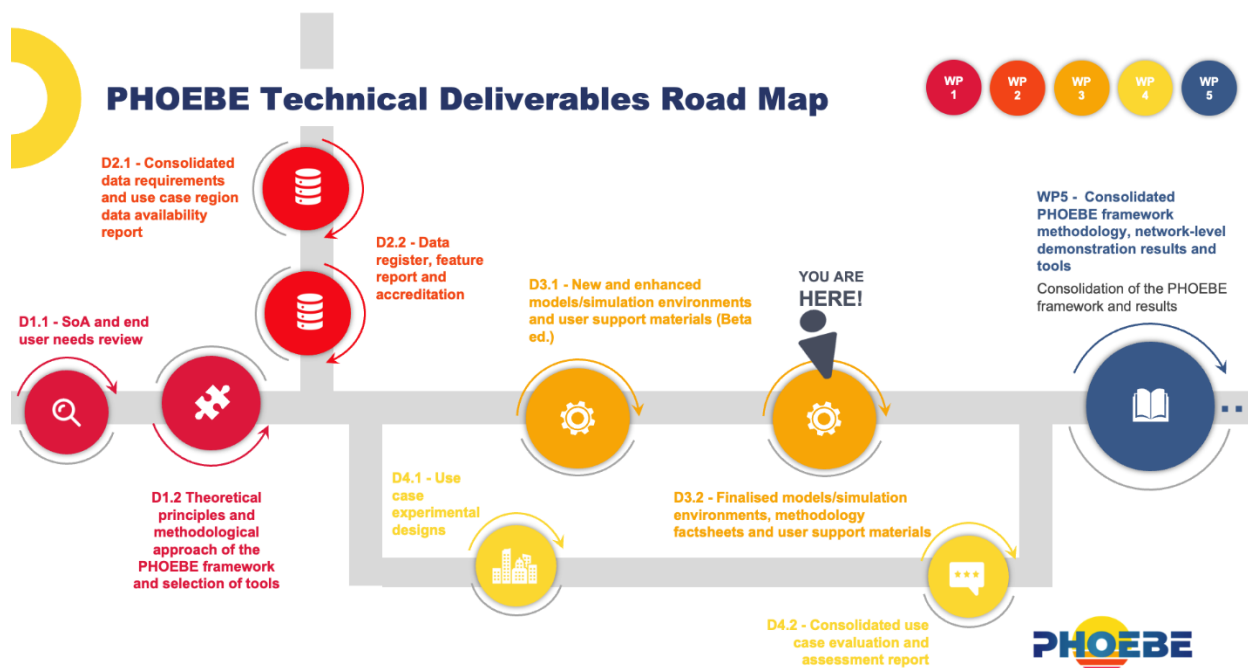


Figure 1-1 PHOEBE Technical Deliverables Road Map

The content of this deliverable is considered sensitive.■



## 2. Development, validation, and implementation of individual components

The chapter content is organised by model component and specifies/describes the overall enhancements/developments of the components when relevant. They are:

- Demand Models,
- Human Behaviour Models,
- Risk Assessment Model and
- Traffic Simulation Model

Note that the development and enhancement of the traffic simulation models are closely linked with the four other components, and they are described throughout the four sub-sections.

### 2.1. Demand Models

This section covers the development of mode choice and induced demand models. It begins with an introduction to the demand models, outlining the steps of model development, such as data needs, procurement, cleaning, and modelling.

Detailed delineation of data needs for mode choice and induced demand models, including stated preference data, survey design, and data collection, is presented subsequently.

The chapter also covers risk calculation methodology utilised for different modes relative to public transport, with detailed statistics for fatalities and serious injuries.

Finally, the parsimonious form of the Multinomial Logit Model (MNL) used for mode choice and induced demand is explained. Use case results for West Midlands, Valencia, and Athens are provided in terms of the model specification (utility functions) and parameter estimates.

#### 2.1.1. Demand Models Development

The demand models encompass two types of models:

- Mode choice model (for generating mode-specific demand)
- Induced demand model (for generating new demand for micro-mobility)

The demand models developed within the project include both mode choice models—which generate demand specific to different travel modes—and induced demand models, which estimate the new demand arising for micro-mobility options.

To build these models, extensive data is required. For discrete choice models like those used in PHOEBE, the primary data sources are stated preference surveys, which can be gathered through supplementary surveys. If surveys are unavailable, they must be planned, piloted, and conducted. Figure 2-1 presents the stages of the demand model development.



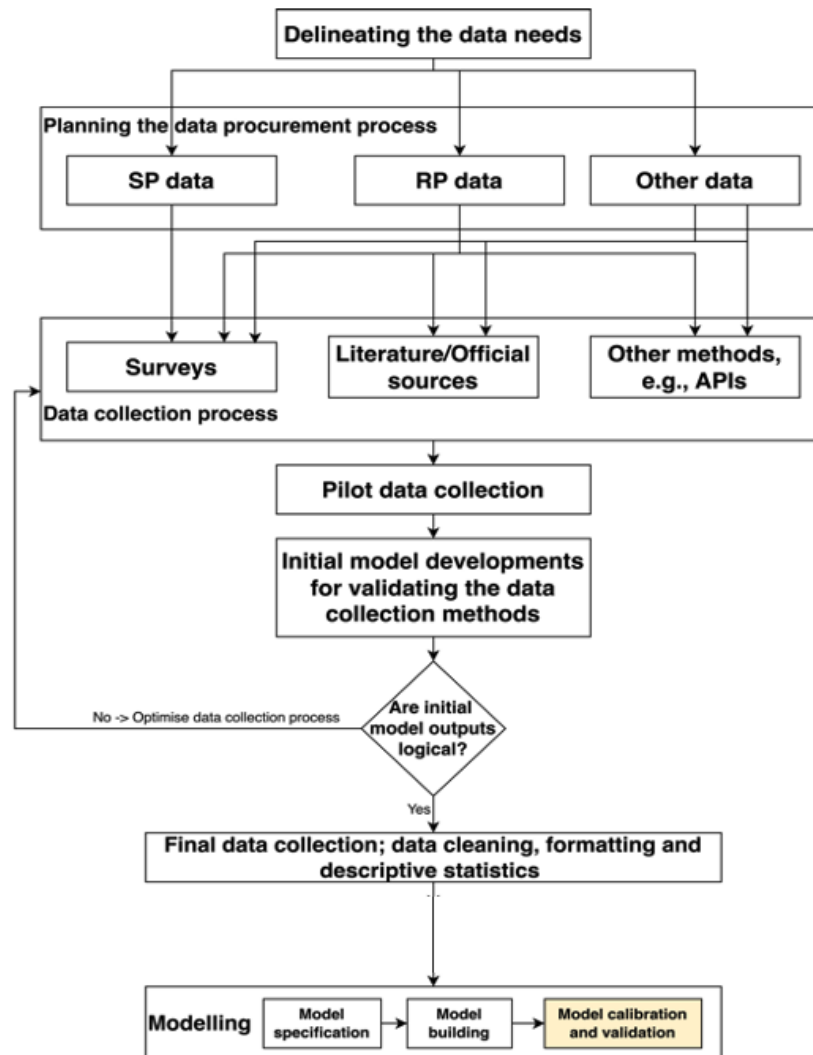


Figure 2-1 Steps of demand model development

The process begins by planning and designing surveys, which includes careful resource management such as budgeting and contracting with survey panel companies. Once the survey is conceived, an initial test run is conducted, typically collecting data from the first fifty participants. The results of this pilot are evaluated to ensure the survey is effective and renders the expected results. If the results are satisfactory, the project proceeds to collect the complete set of data, often targeting approximately five hundred samples representative of the age and gender of the region. Additional details regarding the surveys can be found in [A.1 Demand model surveys and induced demand results](#).

After collection, the data must be cleaned and formatted appropriately. This step involves organizing the data into frames suitable for entry into a choice modelling database. The modelling process itself consists of specifying the utility functions that form the core of the model and then estimating these using specialized software packages, such as Apollo in R, as well as alternatives like Biogeme (Python) and Mlogit (R).

Through this rigorous approach, the resulting robust and parsimonious models are constructed and tailored to replicate the existing and forecast potential demand for different transport modes under various



scenarios. These scenarios are built by changing the predictors of the models. The mode choice and the induced demand models address the following points:

- Socio-demographic factors affecting mode choice and modal shift.
- Risk is associated with the modes affecting mode choice, modal shift, and induced demand.
- Travel/Trip distance affecting mode choice, modal shift, and induced demand.
- Quantifiable intrinsic and extrinsic characteristics associated with the modes, e.g., cost, time, etc., affect mode choice, modal shift, and induced demand.

The mode choice and induced demand models are both macroscopic categories of travel demand models. The models are therefore representative of the whole region of the considered use case. Any part of the use case can thus utilise these models. Hence, the spatial domains for these models are well described by the AIMSUN models as shown below.

In the development of demand models, two distinct types of models are created: the mode choice model and the induced demand model. The mode choice models replicate the modal share of the baseline situation and predict the modal shift under changing scenarios affecting the predictors of these models. The induced demand models generate the extra (more or less) number of trips resulting from the changes in the predictors. The induced demand models are not deployed in the baseline or reference scenario since, in the status quo, there are no changes in the predictors. In any other scenario, the induced models forecast the extra trips caused by changes in predictors, e.g., a change in travel cost. The induced demand models are only deployed for the shared micro-mobility alternative (mode).

### 2.1.2. General Form of the Models (Mode Choice and Induced Demand)

For the mode choice models, the Multinomial Logit Model (MNL) is chosen owing to its simplistic and straightforward nature. The models developed for the frameworks are parsimonious in nature, since the information, e.g., household size, household income, and attitudes, is not present in the subsequent models, namely, microsimulation models of the region. The general form of the MNL model is:

$$P_{ij}=f(S_i,X_j)$$

Where:

- $P_{ij}$ : Probability of  $jj$  extra trips by individual/person group  $ii$
- $f$ : Decision function (e.g., Logit model)
- $S_i$ : Characteristics of the individual/person group  $ii$
- $X_j$ : Differences in characteristics (reasons for induced demand\*) of the alternative  $jj$

Further details are available in **Deliverable D3.1**.

In addition, travel demand has been segmented according to the socio-demographic characteristics relevant to each use case. The socio-demographic variables considered include gender and age, which are representative of the use cases. Specifically, the age groups as captured in the surveys are considered to distribute total travel demand across the three use cases.

For all use cases, gender has been segmented into male and female. The Age group segmentation varies per use case, depending on the sociodemographic information available, and is presented in the table below:



Table 2-1 Age groups per use case

| Use Case           | Age groups                                       |
|--------------------|--------------------------------------------------|
| Athens (EL)        | 18-24, 25-34, 35-44, 45-54, 55-64, and 65+ years |
| Valencia (ES)      | 18-24, 25-34, 35-44, 45-54, 55-69, and 70+ years |
| West Midlands (UK) | 18-24, 25-34, 35-44, 45-54, and 55-69 years      |

### 2.1.3. Induced demand models:

Shared micro-mobility - e-scooters, dockless bikes, and other lightweight vehicles — has changed the way people think about short urban trips. It does more than substitute for private car use or public transit (PT). Travellers often make new journeys out of their general routine that would not have happened otherwise, a phenomenon known as induced demand. A change (generally decrease) in predictors, e.g., travel costs, is responsible for induced demand as shown in the following Figure 2-2.

Accurately forecasting these extra trips is vital for operators planning fleet sizes, cities allocating curb space, and planners evaluating whether micro-mobility advances sustainability goals or shifts travel from greener modes. The model outlined here was explicitly conceived to predict the magnitude of these induced trips and to do so with a single specification that appraises across three distinct deployment scenarios.

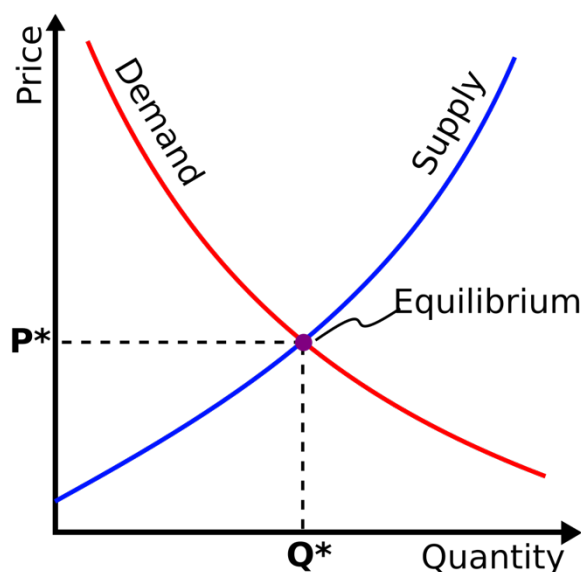


Figure 2-2 Supply and demand curve

Rather than relying on the absolute values of the variables/predictors, the model operates on the *differences* of the variables (e.g., Travel Costs) that travellers perceive when deciding between micro-mobility and their next-best option. Four explanatory constructs capture these perceived deltas: *travel cost*, *in-vehicle time*, *Access-Wait-Egress-Time (AWET)*, and *perceived risk relative to public transit*. Focusing on differences is intuitive: a two-euro ride may seem cheap or expensive depending on the user's baseline, but a two-euro *cheaper* ride is unambiguously attractive. Likewise, a three-minute walk to an e-scooter versus a six-minute wait for a bus is what nudges a pedestrian into trying the device.

The outcome of interest is not binary ("ride" vs. "not ride") but ordinal—e.g., *no additional trips*, *a few occasional extra trips*, or *frequent induced trips*—an *ordered logit* specification is the natural analytical choice. Ordered logit is tailored for dependent variables that carry a ranking but no meaningful cardinal distance between categories. It simultaneously respects that "often" is higher than "sometimes" and "never," while avoiding the spurious precision of treating the labels as evenly spaced numbers. Additionally, the ordered logit formulation delivers interpretable threshold parameters: one can see exactly where the perceived benefit tips an individual from indifference into curiosity, or from curiosity into habitual use.

Since the differences between the variables are identified, a standard model for all three use cases is developed. The details of the induced demand model are presented below.

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#### 2.1.4. Demand Models Testing

Model testing was conducted to ensure the reliability, behavioural plausibility, and policy relevance of the mode choice and induced demand models developed within the PHOEBE framework. Testing covered all three use cases — West Midlands, Valencia, and Athens — and included both quantitative validation and qualitative checks across segmentation groups and scenarios. Following the estimation of MNL models using Apollo in R, each use case was subjected to an internal validation process that entails the examination of coefficient signs, statistical significance, and behavioural elasticity. The parameter estimation tables (e.g., for West Midlands on the slide titled “*Parameter estimates: WM*”) confirmed the expected sensitivity of the input predictors, e.g., travel cost, in-vehicle time, and perceived risk, with consistent negative signs and significance across most variables.

Model fit was assessed using log-likelihood values and McFadden's pseudo- $R^2$ , with typical values indicating acceptable fit for SP-based discrete choice models (MNL in this case). For instance, the model structure diagrams and the segmentation results presented in slides under “*Use Case Results – Valencia*” and “*– Athens*” demonstrate demographic coherence, particularly across gender and age groups. The A.2 Demand Surveys results show the distribution of mode choice and induced demand responses, providing graphical evidence of response variability, which supports robust utility function estimation.

A vital part of the model testing was to determine the good data points obtained through the surveys. Through visual inspection of the results of the survey completion, including time distributions of the responses (e.g., the slide titled “*Survey completion time distribution: West Midlands*”), the low-quality responses, like incomplete responses, lexicographic response patterns, rushed responses, etc., were identified and flagged. Finally, the total number of flagged responses (e.g., 11 responders' responses in WM) was excluded from the model estimation process. These data quality checks enhanced the credibility of model predictions.

The estimated mode choice models were calibrated and validated with the real-world modal split data (e.g., Slide: Model Calibration) provided by the use case leaders. The models (mode choice) are calibrated by adjusting the values of the alternative-specific constants ( $\alpha$ ). The induced demand models were kept uncalibrated since such real-world data are unavailable.

Overall, the testing ensures the models' statistical robustness, transferability across the urban contexts, and integration readiness into the PHOEBE simulation and safety evaluation workflows. Model outputs, including disaggregated demand shifts and induced trip volumes, will be fed into WP3, WP4, and WP5 components for dynamic risk and network-level impact estimation.

Model testing serves as a crucial step to evaluate how effectively the estimated models respond to various scenarios and input changes. While this procedure shares similarities with realism testing—both aiming to assess the plausibility and credibility of model outputs—it is distinct in its specific focus. Model testing does not constitute a complete sensitivity analysis but rather provides a targeted examination of whether the model behaves as expected given the data and context. This approach ensures that the model's predictions are both reliable and aligned with real-world behavioural patterns, thereby reinforcing the integrity and practical value of the modelling framework. Figure 2-3 presents the model testing procedure.



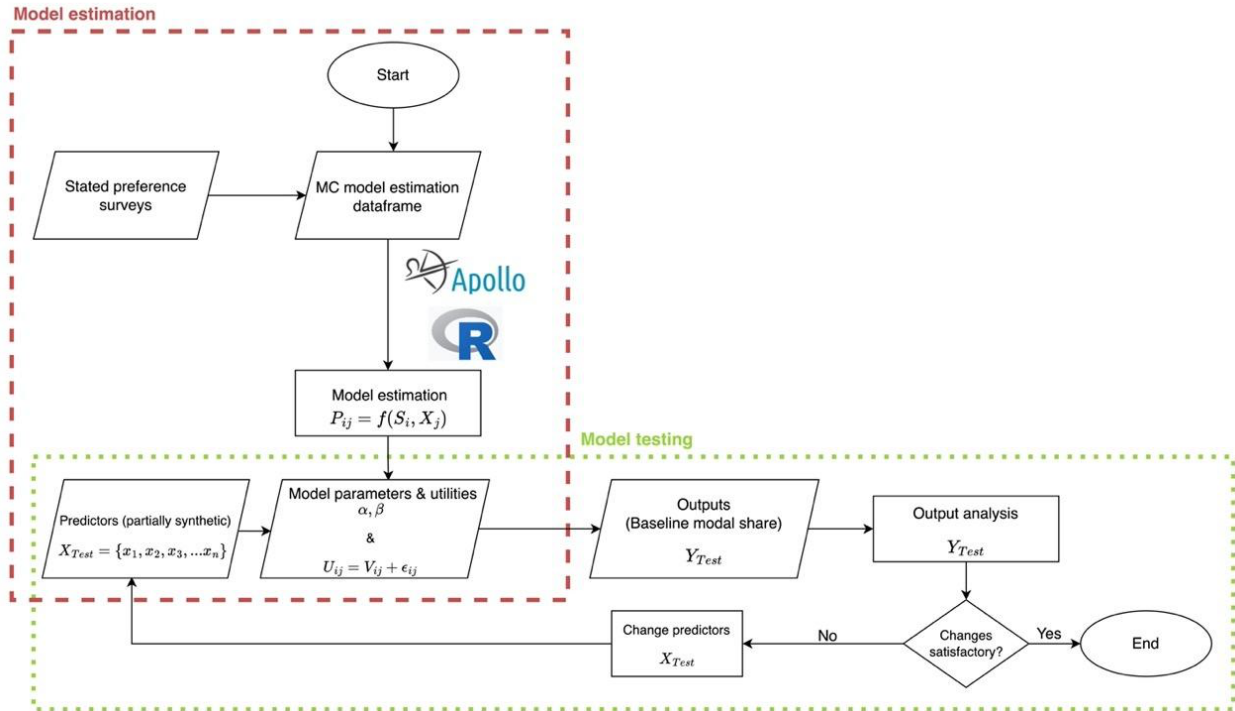


Figure 2-3 Demand model testing procedure

### 2.1.5. Test Case

The estimated models underwent a thorough process of initial testing, followed by calibration to ensure accuracy and relevance. Model testing is conducted with partially synthetic data, allowing for controlled evaluation of performance and reliability in varied conditions. Subsequently, the models are further calibrated using data derived directly from the specific use case, enhancing their alignment with real-world scenarios.

To test the quality of the outputs of the estimated models, a synthetic test case is considered. For this, the West Midlands (UK) Subnetwork A 45 modelling area is chosen owing to the size of the network (A45 subnetwork is the most significant modelling area among the three use cases). To carry out the testing, the following inputs are assumed. These assumptions are derived from the inputs of the survey. The only synthetic part of this process is the trip distances (TD) between the origin and destinations, which were generated by a random number generator with the constraint of the minimum distance as 0,5 miles and maximum being 15 miles (Figure 2-4). The rest of the assumptions are listed below:

- Travel distance: Synthetic (0 to 25 miles), Diagonal matrix (573 x 573)
- Car cost: 0.45 GBP/Mile + Parking charge 3.54 GBP for 2 hours
- PT ticket: 2 GBP for trips ≤ 2 miles, 2.47 GBP for trips > 2 miles
- SM cost: 1.03 GBP (Unlock) + 0.14 GBP/min (Usage)
- Bike cost: 0.09 GBP/Mile
- Avg. Car speed: 23.67 mph
- Avg PT speed: 15.1 mph
- Avg SM speed: 10 mph



- Avg bike speed: 9.1 mph
- Avg walk speed: 2.5 mph
- Risk: PT to Car (2.59), SM (28), Bike (32.72), Walk (9.81)
- AWET Car: 5 min
- AWET PT: 10 min for small trips 13 min for long trips
- AWET SM: 5 min
- AWET Bike: 3 min

Here, the approach ensures that both the robustness and adaptability of the models are scrutinized before proceeding to broader applications. This systematic process not only verifies the model's capacity to simulate realistic travel behaviours and demand patterns but also fine-tunes its predictive capabilities for integration within larger simulation and evaluation frameworks. -

|         | 3778856 | 3778857 | 3778858 | 3778859 | 3778860 | 3778861 | 3778862 | 3778863 | 3778864 | 3778865 | ... | 3779423 | 3779424 | 3779425 | 3779426 |
|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|-----|---------|---------|---------|---------|
| 3778856 | 6.0     | 16.5    | 16.5    | 5.5     | 18.0    | 8.0     | 19.5    | 12.5    | 21.0    | 12.0    | ... | 13.0    | 16.0    | 12.5    | 10.5    |
| 3778857 | 16.5    | 22.0    | 16.5    | 15.0    | 12.0    | 22.0    | 11.0    | 5.0     | 2.5     | 9.5     | ... | 13.5    | 14.5    | 8.0     | 2.5     |
| 3778858 | 16.5    | 16.5    | 17.0    | 11.5    | 20.5    | 19.5    | 4.0     | 3.0     | 7.5     | 2.0     | ... | 12.5    | 11.0    | 18.0    | 3.5     |
| 3778859 | 5.5     | 15.0    | 11.5    | 14.0    | 13.5    | 22.5    | 10.0    | 13.5    | 2.0     | 21.0    | ... | 9.0     | 6.5     | 15.0    | 9.5     |
| 3778860 | 18.0    | 12.0    | 20.5    | 13.5    | 2.0     | 18.5    | 23.5    | 14.5    | 7.0     | 11.0    | ... | 16.5    | 7.5     | 19.0    | 2.5     |
| ...     | ...     | ...     | ...     | ...     | ...     | ...     | ...     | ...     | ...     | ...     | ... | ...     | ...     | ...     | ...     |
| 3779428 | 5.5     | 12.5    | 11.5    | 13.0    | 11.5    | 19.0    | 9.0     | 19.5    | 17.5    | 14.5    | ... | 21.5    | 16.0    | 1.5     | 5.0     |
| 3779429 | 17.0    | 14.5    | 3.5     | 19.5    | 8.5     | 21.5    | 18.0    | 11.5    | 6.0     | 20.0    | ... | 16.0    | 8.0     | 18.5    | 5.0     |
| 3779430 | 9.0     | 8.5     | 13.5    | 16.0    | 22.0    | 10.5    | 8.0     | 3.5     | 12.0    | 2.0     | ... | 9.5     | 17.5    | 19.5    | 12.0    |
| 3779433 | 2.5     | 20.5    | 11.5    | 19.0    | 14.0    | 15.0    | 14.5    | 2.0     | 18.5    | 9.5     | ... | 3.5     | 6.0     | 8.5     | 13.5    |
| 3811708 | 9.0     | 13.5    | 16.0    | 19.0    | 13.0    | 14.0    | 15.0    | 12.5    | 13.0    | 13.5    | ... | 6.0     | 14.0    | 22.0    | 18.0    |

Figure 2-4 Synthetic trip distance (miles) between Origin and Destination for West Midlands.

The testing provided logical outputs in terms of the output segmented OD matrices. This step acted as a coupling between the model estimation and the actual integration procedure.

### 2.1.6. Demand Models Calibration

The calibration of mode choice and induced demand models was carried out using stated preference (SP) and revealed preference (RP) data collected across the three PHOEBE use cases: West Midlands (UK), Valencia (ES), and Athens (EL). Calibration involved tuning the models' specific estimated parameters (alternative specific constants or  $\alpha$ ) to reflect observed travel behaviour and contextual characteristics specific to each urban area, ensuring alignment between empirical data patterns and theoretical utility formulations. The calibration process relied on the real-world modal split data and the travel demand (OD matrices) from the traffic microsimulation (AIMSUN) models, as shown in the next section. The use case leaders provided the real-world modal shares.

For each use case, the step of model calibration began after the estimation of the mode choice models (see Figure 2-5). Model runs were performed on the unsegmented travel demand of the use cases iteratively after changing the alternative-specific coefficient, followed by the calculation of the modal share of the travel demand from the microsimulation models. These synthetic shares were then compared to the real-world modal share data. This process was carried out until a convergence between the synthetic and real-world values was achieved. Sensitivity tests were then carried out to validate the model outputs. This process was not done for the induced demand models since no such real-world data is available.



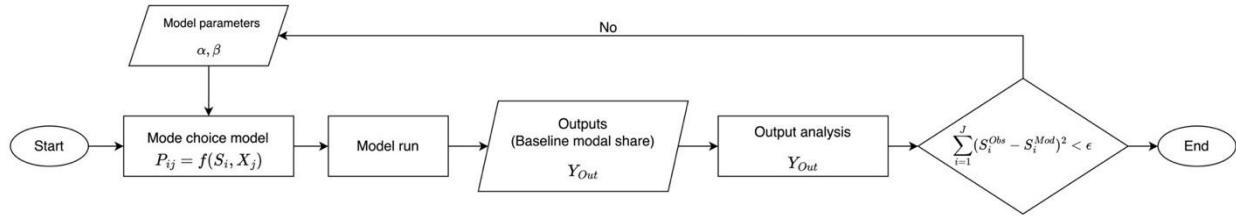


Figure 2-5 Demand model calibration process

Instrumental variable techniques were applied to address potential endogeneity, as outlined in the “Survey Completion Time Distribution” sections. Shortest distance data is used as a proxy for the trip distance impedance during the model runs. This was particularly relevant in aligning model outputs with regional characteristics, such as those seen in the supply networks of the use cases.

Ultimately, calibration ensured that each model captured the specific baseline behavioural context of the corresponding use case while maintaining structural consistency across the project framework. These processes resulted in the calibrated models, which can be directly used for demand forecasting, policy simulation, and integration with PHOEBE’s dynamic safety assessment and traffic modelling environments.

The model calibration process involves two key parameters:

- Alternative Specific Constants (α) – These are systematically adjusted to influence the model's output, specifically the modal share.
- Utility Coefficients (β) – These remain unchanged throughout the calibration process.

After each model run, the resulting modal share is compared against real-world observed data. The calibration continues iteratively until a satisfactory goodness of fit is achieved.

The calibration is guided by an objective function, which ensures that the difference between the observed modal share ( $S_i^{Obs}$ ) and the modelled modal share ( $S_i^{Mod}$ ) for each iteration  $i$  is within a small acceptable threshold ( $\epsilon$ ). Figure 2-6 demonstrates the process.

$$\sum_{i=1}^J (S_i^{Obs} - S_i^{Mod})^2 < \epsilon$$

Where  $i$  is the  $i$ th iteration,  $S_i^{Obs}$  is the observed modal share,  $S_i^{Mod}$  is the modelled modal share, and  $\epsilon$  is a small threshold.

The observed modal share ( $S_i^{Obs}$ ) is obtained through official data sources. Figure 2-6 lists the real-world modal split data (enclosed in the box) used for calibrating the mode choice models for the West Midlands. From this table, the 2021 value is considered for the calibration.



| Mode                 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|----------------------|------|------|------|------|------|------|------|------|------|------|------|------|
| Bus                  | 22.2 | 20.6 | 20.5 | 20.2 | 20.3 | 20.1 | 19.5 | 18.7 | 18.9 | 18.9 | 18.6 | 19.1 |
| Car                  | 60.9 | 58.3 | 57.6 | 58.7 | 58.9 | 57.2 | 57.6 | 57   | 56.9 | 56.9 | 56.1 | 62.1 |
| Rail                 | 10.5 | 11.2 | 11.2 | 11.2 | 11.4 | 13.9 | 13.9 | 14.8 | 15   | 14.4 | 14.7 | 6.9  |
| Light vehicle        | 6.6  | 6.5  | 6.5  | 6.3  | 6.2  | 6.2  | 6.2  | 6.2  | 5.5  | 5.7  | 6.4  | 7.6  |
| Tram                 | 0.8  | 0.9  | 0.8  | 0.8  | 0.6  | 0.2  | 0.4  | 0.8  | 0.9  | 1.1  | 1.1  | 0.9  |
| Heavy vehicle        | 2.5  | 2.3  | 2.1  | 2.1  | 2    | 1.9  | 2    | 2.1  | 2.3  | 2.4  | 2.6  | 3    |
| All public transport | 31.8 | 32.5 | 32.8 | 32.2 | 32.4 | 34.2 | 33.8 | 34.4 | 34.9 | 34.5 | 34.4 | 26.9 |
| Cycle                | 0.4  | 0.5  | 0.5  | 0.6  | 0.5  | 0.5  | 0.4  | 0.4  | 0.4  | 0.5  | 0.6  | 0.5  |

Figure 2-6 WM Real World Modal Split Data (source: Transport of West Midlands, 2023)

### 2.1.7. Demand Model Results Per Use Case

The calibration process described above forms the backbone of demand model (mode choice) development across different urban contexts. For each use case examined in this study, a tailored set of transport modes is incorporated, reflecting local mobility patterns and available infrastructure. The demand model results consist of the utility function and its estimated parameters per use case.

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## 2.2. Human Behaviour Models

The PHOEBE Framework's behavioural models integrate human factors and road user behaviours for traffic microsimulation and road safety assessments. This session outlines the final development of these models based on a set of behavioural surveys that gathered data on road user demographics, past traffic behaviours, and various scenarios related to roadway and traffic conditions.

Within the PHOEBE Framework, the behavioural models incorporate human factors and road users' driving/cycling/and walking behaviours into traffic microsimulation and road safety assessment. This deliverable presents the final development of the 'behavioural models' for the study behaviours within each use-case, based on the Stated Preference (SP) surveys. The SP surveys included questions related to demographics, past behaviours, and included several scenarios covering different roadway geometric and traffic characteristics for various types of locations within the study area of the use cases (described in **Deliverable 3.1**). The behaviours of interest as per the use-cases are presented in Figure 2-7.



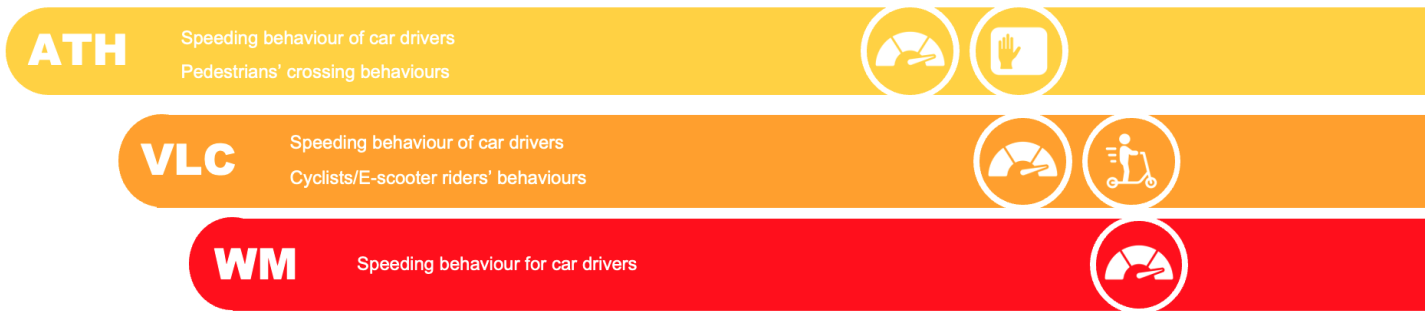


Figure 2-7 Behaviours of interest as per the use-cases

#### 2.2.1. Human Behavioural Models Specifications

The models are all discrete choice models, specifically the Cumulative Logit Mixed Model (CLMM). For the ease of understanding and readability, the models are presented per behaviour. There are three behaviours: speeding behaviour (exceeding the speed limit) of car drivers, red-light violations of micromobility users (bicycles and scooters), and crossing outside of the designated area (CODA) behaviour of pedestrians.

The general form of the equation is:

$$\text{logit}(P(Y_i \leq j | X_i, Z_i)) = \log \frac{P(Y_i \leq j | X_i, Z_i)}{1 - P(Y_i \leq j | X_i, Z_i)} = \tau_j - X_i^T \beta - Z_i^T b$$

The above equation can be simplified to:

$$P = \frac{1}{1 + e^{-(\theta - \beta X)}}$$

where

- P denotes the probability of a particular behaviour,
- X represents explanatory variables in the model,
- $\theta$  and  $\beta$  are model coefficients.

The PHOEBE Behavioural model component also encompasses a second set of models that aim to develop the Crash-Conflict Relationship for Road Safety Assessment.

To ensure the safety outcomes from microsimulation, expressed in terms of road user conflicts, can be meaningfully integrated into iRAP models, which are based on fatal and serious injury (FSI) crashes, it is essential to establish a robust connection between simulated conflicts and actual crashes. This is achieved by developing a predictive relationship using Extreme Value Theory (EVT) models. These EVT models analyse observed crash data alongside simulated conflict occurrences, allowing researchers to estimate the number of crashes associated with each target behaviour identified in the study.

The process begins with the collection of empirical data on road user behaviours and their interactions at selected study locations. This data is gathered through extensive video recordings, capturing the nuances of how drivers, cyclists, and pedestrians behave and interact in various real-world scenarios. Once recorded, these videos are meticulously processed using an advanced tracking logic system, which identifies and quantifies instances of conflict between different road users.



The insights derived from this empirical analysis are then incorporated into the road safety assessment models, serving as vital calibration factors. By aligning simulated conflict data with real-world crash outcomes, the models provide more accurate estimations of fatal and severe injury risks. Ultimately, this approach enhances the reliability of road safety predictions within the PHOEBE Framework, enabling more effective interventions and improvements in traffic safety.

### 2.2.1.1. Crash-Conflict Relationship

The proposed framework is a modular, data-driven methodology designed to detect and quantify traffic safety risks using surrogate safety measures such as TTC and PET. It begins with the ingestion of vehicle-VRU interaction data collected across multiple driving sessions. To preserve temporal continuity, the framework automatically detects session boundaries such as day transitions or discontinuities in frame indices and segments the data accordingly. TTC and PET values are then transformed by inversion to prioritise imminence, such that lower TTCs and PETs, indicative of high-risk conflict scenarios, are mapped to higher surrogate severity. The core anomaly detection stage employs an unsupervised dual-path strategy combining two complementary statistical models: one based on isolation of anomalous behaviour within a high-dimensional feature space, and another rooted in robust covariance estimation to detect multivariate outliers. These models operate independently of crash labels, enabling scalable conflict detection in naturalistic urban settings.

The resulting anomaly candidates are interpreted as surrogate markers of high-risk VRU–vehicle or vehicle–vehicle interactions. To ensure that statistical assumptions underpinning EVT are satisfied, the detected anomalies undergo a two-stage temporal de-clustering procedure. First, only one exceedance is retained per local burst of anomalies to eliminate short-term temporal dependence. Second, a minimum inter-event time gap is imposed to enforce statistical independence between remaining events. This process produces a de-clustered dataset compatible with EVT assumptions. The risk modelling stage proceeds by applying multiple EVT strategies. Block maxima are fitted using the GEV distribution, while exceedances above a calibrated threshold are modelled with the GP distribution. Each model's validity is assessed through diagnostic plots, fit statistics such as the Kolmogorov–Smirnov distance, and information criteria including AIC. When the GP fit proves inadequate, typically due to overly rigid or bounded tails that truncate risk extrapolation, a fallback mechanism is triggered to ensure robustness.

The fallback component introduces a Bayesian variant of the GP model, enabling probabilistic inference of tail risks under uncertainty. All the models are estimated using Markov Chain Monte Carlo (MCMC) sampling with the No-U-Turn Sampler (NUTS), a state-of-the-art adaptive method that optimises both step sizes and sampling trajectories to improve efficiency in complex posterior distributions. All models are trained using two independent chains, each running for 50,000 iterations, with the initial 30,000 samples per chain discarded as burn-in. The remaining 20,000 samples per chain form the basis for posterior inference. Convergence is assessed via diagnostics such as the Gelman–Rubin statistic  $R$ , with thresholds below 1.01 confirming parameter stability. In cases where the Bayesian GP still exhibits limited support, the framework falls back on Generalized Additive Models for Location, Scale, and Shape (GAMLSS), dynamically selecting the best-fitting distribution (e.g., Weibull or lognormal) based on AIC. The final outputs include interpretable tail probability estimates, confidence intervals for crash likelihood, and calibrated TTC/PET thresholds, summarised in diagnostic tables that reflect anomaly detection quality, de-clustering effectiveness, and model fit performance. Collectively, this hybrid EVT framework ensures statistically valid, interpretable, and operationally robust estimation of traffic safety risks in complex urban environments.

The proposed Crash-Conflict Relationship Models Development Framework is a modular, data-driven methodology designed to detect and quantify traffic safety risks using Time-to-Collision (TTC) indicators. Figure 2-8 illustrates the stages involved in the development of the framework.





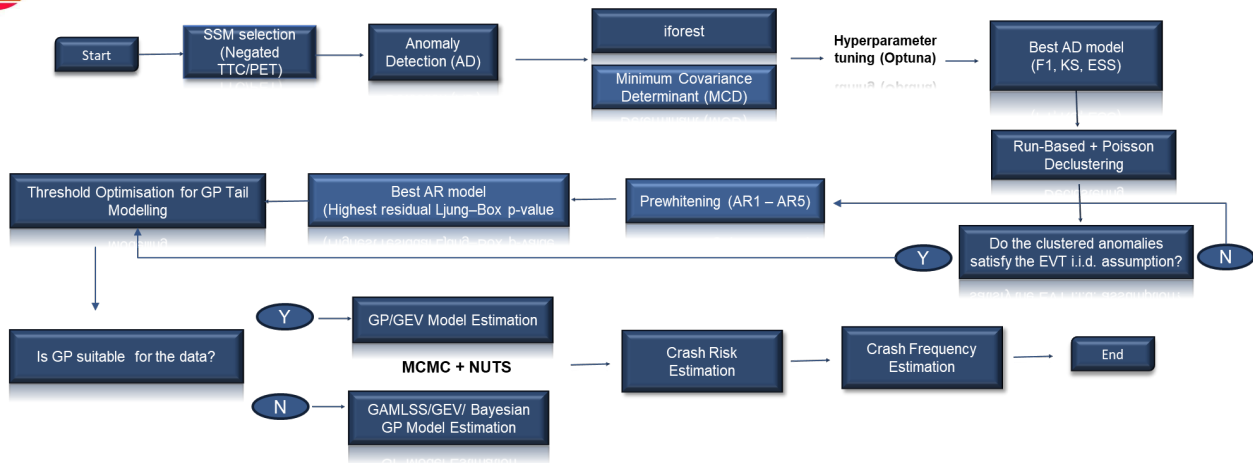


Figure 2-8 Crash-Conflict Relationship Models Development Framework

The process begins by gathering detailed vehicle interaction data from multiple driving sessions. To ensure accurate analysis, the data is automatically segmented based on session boundaries, such as changes in the day or interruptions in the frame sequence.

Once the data is organized, it undergoes preprocessing where TTC and PET values are transformed to highlight risk: lower TTCs and PETs, which indicate higher-risk conflict scenarios, are mapped to a scale that reflects greater surrogate severity.

The core of the analysis focuses on anomaly detection through an unsupervised dual-path approach, utilising two complementary statistical models. The first path isolates anomalous behaviour within a high-dimensional feature space, identifying patterns that deviate significantly from the norm. The second path applies robust covariance estimation to detect multivariate outliers, ensuring that unusual patterns across multiple variables are captured.

To improve the independence of detected anomalies, regular declustering is performed. This step removes short-term dependencies by enforcing a minimum time gap between detected anomalies, ensuring each is statistically independent.

For the modelling of extreme events, the methodology applies Extreme Value Theory (EVT). Specifically, the GEV distribution is used to fit block maxima, while exceedances above a calibrated threshold are modelled with the GP distribution. The quality of these fits is evaluated using the Kolmogorov–Smirnov test and the Akaike Information Criterion (AIC), ensuring the statistical rigor of the approach.

If the primary statistical models are insufficient, a fallback strategy is employed. This involves Bayesian GP modelling to provide robust parameter estimation. If further alternatives are needed, GAMLSS model distributions, such as Weibull or lognormal distributions, are used as the final fallback option.

Through this systematic, data-driven approach, the framework delivers a nuanced and reliable assessment of traffic safety risks, building a strong foundation for further validation and enhancement of human behavioural and risk assessment models.

### 2.2.1.2. Detection of use Case non-compliant behaviours

In the case of Athens, the system employs a comprehensive, multi-step tracking logic to monitor and analyse objects within traffic scenes. Initially, it utilizes an advanced object detection framework based on the YOLOv8 neural network, capable of identifying a wide range of entities, including pedestrians and





vehicles. With each frame of video, the system generates bounding boxes and assigns confidence scores to every detected object, ensuring precise localization.

To maintain consistent tracking of individuals and vehicles across frames, the system applies feature matching techniques. These involve the use of specific metrics such as Intersection over Union (IoU) to measure spatial overlap, and cosine similarity to evaluate the likeness between feature vectors, further enhancing object association accuracy. Figure 2-10 shows an example of the annotation working in one of the Athens captured scenes.

The tracking process is further refined through the application of a Kalman filter, a recursive algorithm that predicts the future positions and velocities of objects, accounting for uncertainties and noise in observational data. This predictive capability is crucial, particularly when objects become temporarily occluded—such as when a pedestrian passes behind a vehicle—ensuring continuity in object trajectories.

When objects re-emerge after occlusion or brief absence, the system leverages a re-identification (Re-ID) network. By analysing visual appearance using features extracted from a ResNet-50 model, the Re-ID network matches objects to their correct histories by comparing their unique feature vectors. This sophisticated approach enables the system to reliably associate newly reappearing objects with their prior identities, thus maintaining the integrity of the tracking data throughout complex and dynamic traffic scenarios.

Two types of behavioural data were collected through video recordings at various study locations within the Athens use-case, including:

- Vehicles Speeding behaviour
- Pedestrians' non-compliant behaviour, including violation of the pedestrian signal and crossing outside the designated areas

Video recordings were systematically carried out at eight distinct locations, capturing both peak and off-peak traffic conditions. Each site was observed for one hour during peak and off-peak hours, with sessions scheduled on both Tuesday and Thursday over the course of two consecutive weeks. Altogether, this meticulous approach resulted in the collection of 64 hours of video footage—amounting to eight hours per location—ensuring a comprehensive dataset for behavioural analysis.

### Speed Calculation

Speed estimation within the study was approached by analysing the movement of each tracked pedestrian or vehicle over time. Specifically, velocity was determined by calculating the change in position—translated into real-world coordinates—across consecutive video frames. To maintain the reliability of these measurements, the analysis introduced maximum plausible speed thresholds: 10 meters per second for pedestrians and 40 meters per second for vehicles. Any speed readings that exceeded these limits were excluded from consideration, thereby minimizing the influence of false detections or data noise. Furthermore, the Median Absolute Deviation (MAD) method was applied to effectively filter out outliers, ensuring that only realistic and representative speed values contributed to the final analysis.

### Time to Collision (TTC) Calculation

In the calculation of Time to Collision (TTC), the system meticulously analyses the relationship between each tracked pedestrian and vehicle. For every possible pair, it determines their respective positions and derives velocity vectors to represent their motion. By comparing these velocity vectors, the algorithm calculates the relative velocity, essentially observing how quickly the pedestrian and vehicle are moving toward or away from one another. When both are on an intersecting path and approaching each other, the TTC is positive, signifying a potential risk of collision within a measurable timeframe. Conversely, if the distance between them is increasing, the TTC becomes infinite, indicating no imminent threat. Throughout each video frame, the system records these values, paying particular attention to the pair with the minimum



TTC, as they represent the highest risk scenario. This focused approach not only enables the identification of critical safety moments but also provides valuable data for developing timely warnings and preventive interventions.

The non-compliant behaviour detection analysis begins with projecting points from the two-dimensional video frames into the real-world ground plane using the homography techniques. This transformation is essential for accurately identifying whether pedestrians or vehicles are located within specific boundaries—such as crosswalks—that are defined by real-world coordinates rather than just pixel positions.

Once the positions have been mapped onto the ground plane, the algorithm evaluates the behaviour of each projected object concerning key Regions of Interest (ROIs), which include important features like crosswalks or the positions of traffic lights. For instance, a pedestrian detected within a crosswalk during a red pedestrian signal is flagged for illegal behaviour; similarly, vehicles entering a crossing area when the pedestrian signal is green are also identified as engaging in a violation.

A dedicated component is responsible for detecting the current state of traffic lights. This is achieved by isolating the relevant region within the video frame and applying colour segmentation algorithms to determine whether the light is red or green for pedestrians. This sequence of processes allows for precise behavioural analysis of both pedestrians and vehicles, ensuring that compliance with traffic signals and crosswalk usage is rigorously monitored and accurately recorded.

#### Non-compliant behaviour detections

The process of detecting non-compliant behaviour begins by projecting points from the two-dimensional video frames onto the real-world ground plane using the homography techniques. This transformation is crucial for accurately determining whether pedestrians or vehicles occupy specific areas, such as crosswalks, which are defined by real-world coordinates.

Once the positions are mapped, the algorithm assesses the behaviour of each projected object for key regions of interest, like crosswalks and the locations of traffic lights (see Figure 2-9). If a pedestrian is observed within a crosswalk during a red signal, their behaviour is marked as a violation; similarly, vehicles entering the crossing during a green pedestrian light are identified as engaging in illegal behaviour. Integral to this process is a dedicated traffic light detection system: by isolating the relevant regions within each video frame and applying colour segmentation, the system reliably determines whether the pedestrian signal is red or green. This sequence of steps enables precise and thorough analysis of compliance with traffic regulations, ensuring that both pedestrian and vehicle behaviours are rigorously monitored and recorded.

understanding. A satellite image—specifically a static Google Maps snapshot—served as the foundational reference frame, providing a real-world spatial context of the monitored area. On this map, the positions of pedestrians and vehicles, detected in the street-level video, were overlaid to represent their trajectories and locations accurately<sup>1</sup>.

The process began with the selection of an overhead satellite image of the observed area to offer a comprehensive base for visualization. Through the homograph transformation, the system projected the real-time positions of both pedestrians and vehicles detected in the video onto the corresponding locations on the static map. This mathematical transformation ensured that each object's position in the video aligned precisely with its actual coordinates in the real world.

As the system tracked pedestrians and vehicles over time, their movements appeared as dynamically updated points or icons on the static map. This approach provided a clear, overhead view, making it easy to visualize the paths and interactions of all moving objects throughout the monitored area.

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<sup>1</sup> See a demonstration video [here](#).





Figure 2-9 Roadside Annotated Video<sup>2</sup>

In addition to dynamic video analysis, detection was also conducted using static maps to enhance spatial

Therefore, the algorithm operates by tracking all pedestrians and vehicles present within the monitored area, carefully analysing their movements and interactions. It assesses whether each road user is behaving under traffic regulations, such as obeying traffic lights or remaining within crosswalk boundaries, or if non-compliant actions are taking place. Central to its safety analysis is the calculation of TTC, which is performed using a sophisticated, multi-stage approach. By integrating real-time video with advanced tracking techniques, the system enables the continuous detection, monitoring, and evaluation of traffic participants. This comprehensive process not only supports the identification of risky behaviours but also enhances the overall safety and efficiency of urban traffic management.

Within the Valencia use case, empirical data were gathered to shed light on the interactions between vehicles and micro-mobility users, particularly during potentially critical situations such as conflicts and red-light violations. The study involved video recording the trajectories of both vehicles and micro-mobility users at three different intersections across various weekday periods. This continuous observation enabled the detection of instances where micro-mobility users failed to comply with red light signals, as well as the identification and characterization of interactions, sometimes escalating into potential conflicts, between these users and vehicles. The collected trajectory data underwent further analysis to pinpoint specific behaviours, offering valuable insights into the prevalence and nature of red light running and the dynamics of intermodal interactions within the urban traffic environment.

The flowchart in Figure 2-10 outlines a four-step data filtering process aimed at identifying specific user behaviours. It begins by selecting only those data entries where the class is either "person" or "bicycle", ensuring the analysis focuses on relevant user types. Next, it removes users who exhibit high horizontal displacement, defined as movement exceeding a certain threshold, to eliminate outliers or irrelevant patterns. The third step narrows the dataset further by retaining only those entries that fall within a predefined Region of Interest (ROI), applying a spatial constraint to the analysis. Finally, within this ROI, the data is filtered once more to isolate only those users who cross the red light, effectively identifying potential traffic violations.

<sup>2</sup>A demonstration video can be found [here](#)



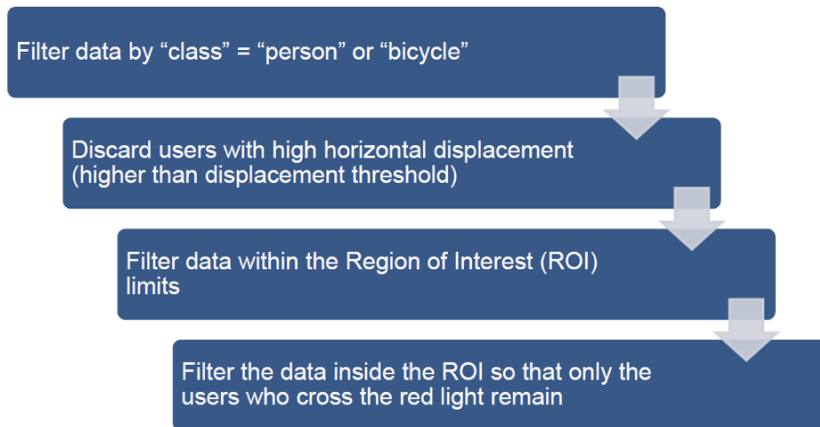


Figure 2-10 Valencia framework for real-life behaviour tracking

After manual review, the analysis yields a dataset containing trajectory information.

- ID: Identification of the user.
- Intersection: Intersection ID.
- Day/Time: Weekday and time of day (e.g., MM = Monday Morning).
- Type: Indicates whether the crossing occurred with the traffic light on red (R) or if it was a traffic conflict (TC).
- TrajectoryReference: Reference point of the trajectory (e.g., F = Frontal).
- Gender: Gender of the micromobility user (e.g., M = Male).
- VehicleType: Type of micromobility vehicle (e.g., B = Bicycle).
- HelmetUse: Whether the micromobility user was wearing a helmet.
- VehicleGAP(s): Time gap in seconds between the micromobility user crossing and a vehicle passing on the roadway.
- Comments: A free-text field for additional comments.
- Trajectory (x, y, t): The trajectory data represented by x and y coordinates over time t in the video.

In the West Midlands use case, a detailed study was conducted on vehicle speeding behaviours using an empirical dataset collected in 2022 by The Floow Limited, a leading provider of telematics services for the UK insurance sector. The data was gathered through in-vehicle devices such as on-board diagnostic (OBD) units and smartphones, which captured speed and positional information every second via the Global Navigation Satellite System (GNSS). Unlike traditional methods that might be affected by inaccuracies in positioning, the GNSS-based approach determines speed by analysing the Doppler shift of the satellite signal relative to the vehicle's movement, resulting in exact speed measurements.

The speeding data were organized to show individual proportions of speeding, as well as key statistical percentiles—specifically, the 50th (median) and 85th percentile speeds—across various road sections within the study area. This structured format allowed for a nuanced understanding of how frequently and to what extent vehicles exceeded speed limits, laying the groundwork for subsequent validation of human behavioral and risk assessment models.

#### 2.2.2. Human Behavioural Models Validation

This diagram presented in Figure 2-11 is a comprehensive framework for validating road user behaviour models, integrating both survey-based insights and empirical data. The process begins with the development of behavioural models, informed by SP surveys. These models assume that the survey sample is representative of the city's population and are validated using aggregated telematics or video



data. The second stage involves validating behaviours within Aimsun microsimulation, comparing simulated behaviours and conflicts with actual observations when available. The final step focuses on integrating behavioural factors into iRAP models, where estimated FSIs are validated against real-world FSI data. Together, these steps ensure that behavioural models are not only theoretically sound but also practically reliable for traffic safety analysis and infrastructure planning.

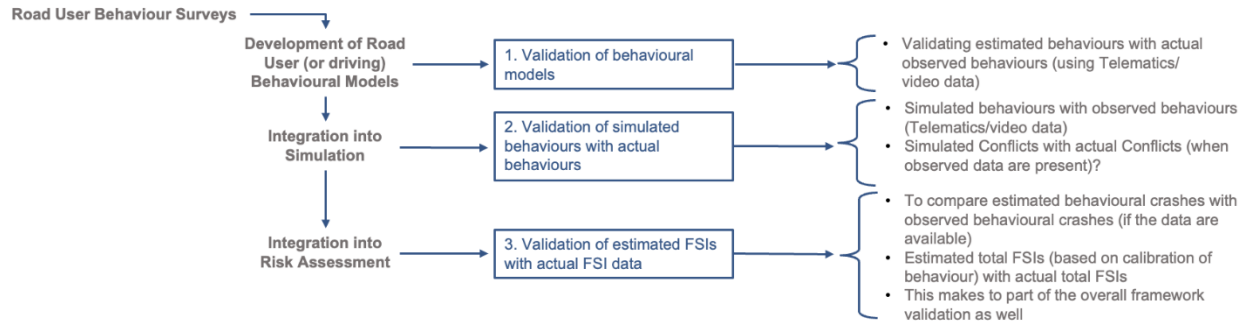


Figure 2-11 Human Behavioural models validation process

To ensure comprehensive validation, six Aimsun road segments were randomly selected from the West Midlands network for each location, with selection criteria designed to guarantee representation across the risk assessment, simulation models, and telematics datasets, thereby maximizing the variability of the survey scenarios included. The resulting combined dataset was produced by spatially integrating the data from all three sources and linking it to an additional dataset containing telematics-measured speeding proportions before being consolidated in an Excel file for analysis. To determine actual speeding proportions, the corresponding telematic sections' speeding data were averaged for each simulation segment, distinguishing between peak and off-peak hours defined as three hours in both the morning and afternoon for peak, and midday and night for off-peak, each lasting three hours. The computed values, along with their 95% confidence intervals, were recorded in the Excel file. For the survey-based proportions, probabilities of participant scenario selection were estimated using a behavioral equation that incorporated variables such as traffic conditions, speed limits, and driving history. These probabilities were then aggregated and averaged for peak and off-peak periods. Calibration Factors (CFs) for both traffic conditions were calculated by dividing observed speeding proportions by those derived from the survey, and the final CF for each location was obtained by averaging across all available segments. This process provided a robust foundation for validating behavioral models against real-world observations.

For micromobility users in Valencia, a total of three intersections were analysed. The actual non-compliant behaviour proportions, specifically red signal violations, were computed based on video-extracted data. The rate of these behaviours was determined by dividing the number of observed red light violations by the total number of crossings for each intersection, separately for peak and off-peak traffic hours. Additionally, 95% CIs were calculated for these observed values to quantify variability in non-compliance rates.

For the survey-derived proportions, a methodology similar to that used in the WM case was applied. Relevant survey scenarios were selected for each intersection, ensuring alignment with real-world conditions. The probability of a red-light violation in each scenario was estimated using a behavioural model that incorporated road characteristics, traffic conditions, and individual-level factors. The resulting probabilities of all participants were then aggregated, and their average across the selected scenarios was computed separately for peak and off-peak traffic hours. CFs were also calculated similarly to the WM case.

The results of the validation process are presented in A.3 Behavioural survey procedures within PHOEBE.





### 2.2.3. Human Behavioural Models Results per Use Case

In the subsequent analysis, two main statistical modeling approaches were developed to investigate behavioral patterns within the use cases. Firstly, discrete choice models were constructed to estimate the likelihood of specific behaviors occurring, drawing upon data gathered from the SP surveys. Additionally, EVT models were employed to examine the correlation between conflicts arising from the studied behaviors and identified through the analysis of simulated road user trajectories and actual crash data recorded historically.

#### 2.2.3.1. Athens

The range of behaviors analyzed includes the tendency of car drivers to exceed speed limits, pedestrians' propensity to cross at red lights, and the frequency with which pedestrians cross the road outside of designated areas. It is important to note that, for this deliverable, only pedestrian behaviours have been incorporated into the crash-conflict modelling, allowing for a focused examination of their impact on road safety outcomes.

Table 2-7 presents the distribution of variables of the utility equations presented below.

Table 2-7 Human behavioural model variables distribution

| Variable                                       | Description                                                                          | Type                           | Distribution                                                               |
|------------------------------------------------|--------------------------------------------------------------------------------------|--------------------------------|----------------------------------------------------------------------------|
| Crossing Width                                 | Width of the crossing facility                                                       | Binary<br>0: Narrow<br>1: Wide | This variable comes from the network. No distribution required.            |
| Traffic                                        | Traffic (condition) at the intersection approach (with crossing)                     | Binary<br>0: Low<br>1: High    | This variable comes from the traffic simulation. No distribution required. |
| Distance to Approaching Vehicle(s)             | Distance of an approaching vehicle to a micromobility user at the crossing           | Binary<br>0: Close<br>1: Far   | This variable comes from the traffic simulation. No distribution required. |
| Social Value Orientation                       | Personal characteristics of a micromobility user                                     | Continuous (degree)            |                                                                            |
| Age                                            | The age of a micromobility user                                                      | Continuous                     |                                                                            |
| Past Behaviour: Red Light Running on Crossings | Past red light running events by a micromobility user at marked crossings (scale)    | Continuous (Likert scale)      |                                                                            |
| Past Behaviour: Riding out of Bicycle Lane     | Past events by a micromobility user involving riding out of the bicycle lane (scale) | Continuous (Likert scale)      |                                                                            |

Athens – Speeding Behaviour of Car Drivers



**ATH**



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#### Athens – Red Light Running Behaviour of Pedestrians

Table 2-- 9 presents the statistical estimates along with confidence intervals and significance values for the predictors associated with pedestrians' red light running behaviour. The model indicates that pedestrians are less likely to engage in red light running when traffic is heavy or the crossing width is wide, suggesting that perceived risk discourages violations. Conversely, being in a rush significantly increases the likelihood of running a red light. Among individual factors, younger pedestrians are more prone to such behaviour. Additionally, those with a history of red light violations or a tendency to cross without looking when in a hurry are more likely to repeat this risky behaviour, reflecting habitual or impulsive tendencies.

The equations are presented below.

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#### Athens – Pedestrian Behaviour of Crossing Outside the Designated Area

The Table 2-10 presents the statistical estimates along with confidence intervals and significance values for the predictors associated with pedestrians crossing outside of the designated areas. The model suggests that pedestrians are less likely to cross outside designated areas when traffic is heavy or the crossing is wide, indicating a deterrent effect of perceived risk and increased exposure time. In contrast, crossing on two-way roads and being distracted while crossing are both associated with a higher likelihood of this behaviour. Younger pedestrians and those with lower prosocial/altruistic (lower values of SVO) orientations are more prone to crossing outside designated areas, highlighting the role of both age and social values. Additionally, individuals with a history of crossing despite oncoming traffic are more likely to repeat this behaviour, suggesting a pattern of risk-taking tendencies.

The equations are presented below.

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#### Athens – Crash- Conflict Models

As mentioned previously, the framework detects session boundaries and transforms TTC values to prioritise imminent conflicts. A dual-path anomaly detection stage, powered by a hyperparameter-optimised Isolation Forest and robust covariance model, identifies high-risk interactions with strong recall and precision. Temporal declustering using a run-based filter and Poisson gap enforces statistical independence, enabling valid EVT-based tail modelling. Threshold selection for GP fitting is guided by diagnostic criteria and confirmed using mean residual life plots. All EVT models (GEV, GP, and Bayesian GP) are estimated via MCMC, with convergence and tail shape thoroughly assessed. When GP assumptions are violated, a GAMLSS fallback ensures support compliance. While Bayesian and fallback models are not used directly for prediction, they validate bounded tail behaviour and strengthen inference. The final framework outputs calibrated TTC thresholds and crash likelihood estimates, ensuring robust, interpretable, and statistically



grounded conflict risk assessment. For the sake of space, here are the results for only one location. The results for the other locations can be found in complementary documents<sup>3</sup>.

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### 2.2.3.2. Valencia

In the context of the Valencia use case, the study developed and applied two main types of statistical models to better understand user behaviors and their implications for road safety. First, discrete choice models were employed to estimate the likelihood of individuals exhibiting certain behaviors, such as speeding among car drivers. These models provide insight into how frequently specific risky actions may occur within the observed population. Additionally, EVT models were utilized to explore the connection between observed conflicts—arising from these study behaviors and detected through the analysis of simulated trajectories of road users—and actual crash records from historical data. By evaluating these relationships, the research aims to bridge the gap between simulated conflict events and real-world crash occurrences, thereby enhancing the accuracy of risk predictions.

The key behaviors investigated in this framework include the speeding tendencies of car drivers and micromobility users' red light violations. This foundation sets the stage for further examination of micromobility users, such as cyclists and e-scooter riders, particularly their red-light violation patterns, as part of the broader risk assessment and modeling efforts.

As part of this deliverable, only micro-mobility users' red light violation behaviour has been used for the crash-conflict modelling.

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#### Valencia - Speeding behaviour of car drivers

The Table 2-14 presents the statistical estimates along with confidence intervals and significance values for the predictors associated with speeding behaviour of car drivers. The model indicates that self-reported speeding is less likely in high-traffic environments and on roads with lower posted speed limits, suggesting that contextual constraints and enforcement expectations play a deterrent role. In contrast, drivers are more likely to report speeding on multi-lane roads and in the presence of physical medians, which may create a perceived opportunity for higher speeds. Younger age and higher weekly driving exposure are both associated with increased likelihood of speeding, pointing to experience and behavioural tendencies. Importantly, a history of disregarding minimum headway is a strong predictor of current speeding behaviour, reflecting a broader pattern of risk-prone driving. Finally, the presence of speed radars is strongly associated with reduced speeding, reinforcing their preventive effect.

The equations are presented below.

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<sup>3</sup> This content has been classified as sensitive and is not included in the public version. To request access, please contact the PHOEBE Project team.





This content has been classified as sensitive and is not included in the public version. To request access, please contact the PHOEBE Project team.

### Valencia - Red Light Running Behaviour by Micromobility Users

The Table 2-15 presents the statistical estimates along with confidence intervals and significance values for the predictors associated with red light running behaviour by micromobility users. The model shows that red light running among micromobility users is less likely when crossings are wide and traffic is heavy, suggesting that greater exposure and risk perception discourage violations. In contrast, red light running is more likely when approaching vehicles are perceived to be far away, indicating risk-taking based on subjective distance judgments. Individual characteristics also influence behaviour: younger users and those with lower prosocial orientation (SVO) are more likely to engage in violations. Past risky behaviours, such as previous red light running and riding outside designated bicycle lanes, are strong predictors of current violations, reflecting consistent patterns of non-compliance.

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### Crash-Conflict Relationship for Valencia Use-Case

Using the observed data on conflicts (between vehicles and micromobility users) from each of the study locations (shown below) within the Valencia use-case, as well as utilizing the actual historic crash data on these locations, a crash-conflict relationship was developed for each study location. Here, we are going to present the example of intersection 1 - Primado Reig - Dr. Gómez Ferrer: The results for the other can be found in complementary document<sup>4</sup>.

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### 2.2.3.3. West Midlands

The following section presents a discrete choice model developed for speeding behaviour (study behaviour) within the West Midlands use-case, providing the probability of speeding based on the data from stated preference surveys. Table 2-2 presents the variable distributions of the utility equations presented below.

Table 2-2 Human behavioural model variables distribution for West Midlands

| Variable | Description                           | Type                      | Distribution                                                               |
|----------|---------------------------------------|---------------------------|----------------------------------------------------------------------------|
| Traffic  | Traffic (condition) at a road segment | Binary<br>0:Low<br>1:High | This variable comes from the traffic simulation. No distribution required. |

<sup>4</sup> This content has been classified as sensitive and is not included in the public version. To request access, please contact the PHOEBE Project team.



| Variable                               | Description                               | Type                           | Distribution                                                    |
|----------------------------------------|-------------------------------------------|--------------------------------|-----------------------------------------------------------------|
| Speed Camera                           | Presence of a speed camera                | Binary<br>0:No<br>1:Yes        | This variable comes from the network. No distribution required. |
| Speed Limit (30mph)                    | Speed limit on the road (segment)         | Binary<br>0:20mph<br>1:30mph   | This variable comes from the network. No distribution required. |
| Speed Limit (40mph)                    | Speed limit on the road (segment)         | Binary<br>0:20mph<br>1:40mph   | This variable comes from the network. No distribution required. |
| Sex                                    | The sex of a driver                       | Binary<br>0: female<br>1: male |                                                                 |
| Social Value Orientation               | Personal characteristics of the driver    | Continuous (degree)            |                                                                 |
| Past Behaviour: Speed Limit Violations | Past speed limit violations by the driver | Continuous (Likert scale)      |                                                                 |

#### West Midlands - Speeding behaviour of car drivers

Table 2-19 shows that self-reported speeding is significantly less likely under high-traffic conditions, in areas with lower posted speed limits, and in the presence of speed cameras, indicating that both environmental constraints and enforcement mechanisms effectively reduce violations. Male drivers are more likely to report speeding than female drivers, while individuals with stronger prosocial orientations (SVO) are less likely to engage in such behaviour. A history of disregarding speed limits in residential areas strongly predicts current violations, highlighting behavioural consistency in risk-prone driving patterns.

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## 2.3. Risk Assessment Models

This section covers various aspects of the Risk Assessment Models Enhancements within the PHOEBE Framework. The focus is on enhancing road safety and improving risk estimation for vulnerable road users (VRUs) such as pedestrians and bicyclists.

The Risk Assessment Models include the iRAP Star Ratings and CycleRAP models, which evaluate the risk of road infrastructure and provide safety analysis for routes used by bicyclists. The models also discuss the dynamic inputs for road safety assessment, including operating speed parameters and flow dynamics.

Additionally, the Fatal and Serious Injury (FSI) estimation models, calibration procedures, and the impact of speed variability on road safety are detailed.



Finally, the chapter covers the testing and validation of risk assessment models, including the results for various use cases and feedback from validation forms.

### 2.3.1. Risk Assessment Models Enhancements for PHOEBE

The iRAP Star Rating safety assessment models—which include both the Star Rating system and the Fatal and Serious Injury (FSI) Estimation models—have undergone significant updates to align with PHOEBE's guiding principles. One of the main advancements is the enhancement of predictive safety capabilities, particularly focused on urban road networks where the safety of VRUs, like pedestrians and bicyclists, is essential. These models have also been optimized to leverage high-quality data derived from artificial intelligence, machine learning techniques, and big data, resulting in more accurate and dynamic risk estimations.

The iRAP Star Rating model evaluates the risk of road infrastructure, which determines the likelihood and severity of road crashes for four types of road users: vehicle occupants, motorcyclists, pedestrians, and bicyclists. Star Ratings categorise over 50 different road attributes to provide a simple and objective measure of the level of safety that is 'built-in' to the road. Five-star roads are the safest, while one-star roads are the least safe. All use cases within the PHOEBE initiative were evaluated utilizing the upgraded Star Rating model (v.3.10). The Star Rating model (v.3.10) was also the one examined during the integration phase.

The CycleRAP model was employed in the PHOEBE project to gain deeper insights into conflicts involving bicyclists in the West Midlands and Valencia use cases. These two cases specifically target the experiences of bicyclists and users of light mobility. In this report, the results will focus on the Star Rating model, but A.5 Risk Assessment Model – CycleRAP FSIs presents the enhancements of the CycleRAP model conducted as part of the PHOEBE Project.

**Deliverable D3.1** provides a detailed summary of the improvements made to the Star Rating Models for PHOEBE. Among these enhancements are the adoption of 1 km/h incremental speed measurements, including the consideration of lower speeds, and a comprehensive review of speed-related risk factors. The contributing factors and risk scores have also been re-evaluated, leading to more accurate assessments. Notably, a new crash category for cyclists—mid-block crossings—has been introduced, alongside refined risk factors for both pedestrian crossings and along-path scenarios. The number of crossing and intersection categories has been expanded, and greater attention is now given to the quality of sidewalks and crossings. Star Ratings are now provided in decimal form, offering more nuanced insights, and there is also an option to base these ratings solely on operating speeds.

The final structure of the pedestrians and bicyclist model is presented in Figure 2-12. The elements highlighted with 'new' are the model updates developed by the PHOEBE enhancements team.

### 2.3.2. Risk Assessment Models Preparation for Dynamic Inputs

The enhancements to the model's structure outlined above lay the foundation for integrating dynamic inputs, forging a direct connection between outputs from traffic simulations and the risk assessment models. The PHOEBE framework highlights speed and traffic flow as key factors linking simulation data to road safety evaluation.

Previously, the model primarily relied on 85th percentile and mean free-flow speeds, as well as AADT for vehicles and peak hour flows for pedestrians and bicyclists. However, simulation outputs generate values at much finer temporal resolutions, often in intervals shorter than an hour. Recognizing that hourly values provide greater analytical granularity and interpretability, a series of enhancements were introduced to the risk assessment model. These improvements now allow the model to accommodate and effectively analyze more detailed, dynamic datasets, strengthening the link between real-world traffic conditions and robust safety assessments.



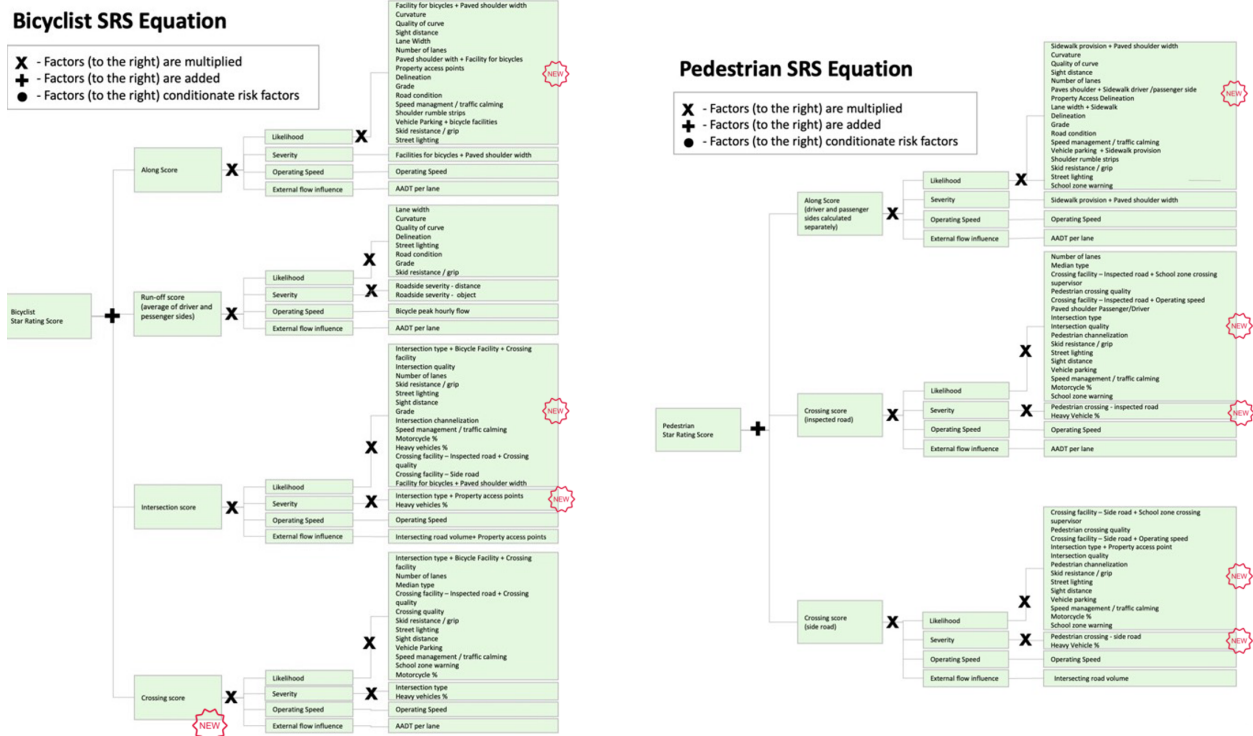


Figure 2-12 Final structure of the pedestrians and bicyclist model

### Operating speeds

The charts show how operating speed parameters change during different stages of the Valencia case study assessment for the Red Corridor. The blue line represents values from static results obtained through actual measurements within the network. The orange line shows speed values generated by simulations for Intervention 1, using the v3.02 specification for operating speed, where speed values are entered into the model in 5 km/h increments. The red line reflects the same dataset as the orange line but uses the v3.10 specifications, where speed values are incorporated into the model in 1 km/h increments.

The simulation's 1 km/h increments and dynamic inputs allow for a more thorough analysis of driving speed trends. Since speed is a crucial risk factor for road safety, having more precise speed measurements enables a more accurate risk assessment.

### Vehicle flows

The Star Rating models use AADT per lane to assess the change in risk associated with motorised vehicles density for the network. Given that the simulation addresses various periods (typically 15-minute intervals), a conversion method must be considered to integrate simulation flows into the risk evaluation.

The Star Rating models utilize AADT per lane to evaluate how changes in motor vehicle density influence network risk. Because the simulation spans multiple time intervals—typically in 15-minute segments—a conversion approach is necessary to incorporate these simulated flows into the risk assessment process accurately.

Understanding the dynamics of hourly vehicle flows is crucial for several reasons:

- Accurate crash risk modelling: accounting for speed variability, congestion, and exposure.



- Infrastructure resilience: Simulating how networks respond to peak loads and disruptions.
- Strategic planning: forecasting future demand under uncertainty and guiding investment

To enhance replicability, a method was chosen to convert simulated hourly vehicle flows into an equivalent daily flow. The calculation for the AADT equivalent uses the total vehicle count over a 15-minute interval (N15min). It applies an equivalence rate,  $t$ , which represents how much an average hourly flow contributes to the overall daily traffic. This approach ensures that the simulation data can be accurately compared with AADT figures for risk assessment and infrastructure planning.

$$AADT_{equivalent} = \frac{\sum_{i=1}^4 N_{15min}}{t}$$

The value of  $t$  for the Athens and WM use cases was determined from both manual counting and telematics data, resulting in  $t = 0.07$  for each case. For Valencia,  $t$  was established through sensitivity analysis, which involved comparing simulated flow data with accurate AADT figures. The chart shows the comparison between the flow of H1 and the corresponding AADT data using different  $t$  values. The following Figure 2-13 displays the use of  $t$  values of 0.07 and 0.05 over four simulated hours. Based on these slides,  $t = 0.05$  was used for Valencia assessments.

### 2.3.3. Fatal and Severe Injuries Models Enhancements

FSI Estimates draw on the road attribute data used for Star Ratings, flow data for each of the road user groups, and network-level crash data to provide an estimation of FSIs along each segment of road and support the prioritisation of investment. The FSIs calculation procedure is described in **Deliverable 1.2 - section 2.5.2.1**.

In essence, the FSIs methodology utilizes crash data to fine-tune estimations by leveraging infrastructure elements and exposure crash modification factors. This calibration process ensures that various factors influencing road safety (e.g., behavioural aspects, vehicle maintenance conditions, weather conditions, etc) are adequately accounted for in the estimations.

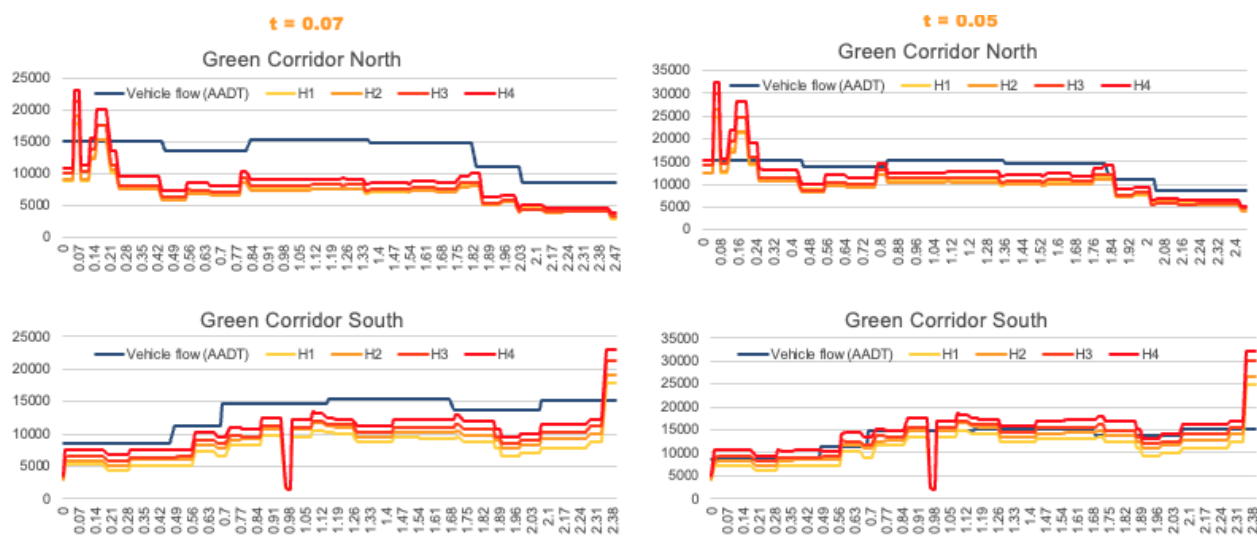


Figure 2-13  $t$  values for the Valencia Green North corridor

When calculating FSIs for the post-intervention scenario, the model maintains the calibration from the pre-intervention situation, solely accounting for reductions in FSIs based on changes in infrastructure components. Therefore, in the PHOEBE framework, the FSIs' estimations will be calibrated based on two components:

- Historical crash data
- Conflicts due to specific behaviour (transform into a crash through the methodology presented in Section 2.2)

Therefore, the PHOEBE project improved FSIs through two distinct methods:

- Introducing an extra calibration factor across all user groups to address speeding tendencies and the variability of speeds within the segment.
- Adding a new calibration factor (or refining current calibration factors) to target pedestrian and bicyclist/micromobility violation behaviours specifically.

#### FSIs Updates to Account for Speeding Behaviour – The Theory

Variability in vehicle speeds within a traffic stream creates significant safety concerns. Road segments exhibiting high speed variability—where vehicles are travelling at markedly different speeds—pose unique dangers. Such conditions elevate the likelihood of rear-end collisions, complicated lane changes, and overtaking maneuvers, and increase the risk of side-impact crashes (Kalambay, Pulugurtha, 2024; Apostoleris et al., 2023). Variability in vehicle speeds within a traffic stream creates significant safety concerns. Road segments exhibiting high speed variability—where vehicles are traveling at markedly different speeds—pose unique dangers. Such conditions elevate the likelihood of rear-end collisions, complicated lane changes, and overtaking maneuvers, and increase the risk of side-impact crashes.

The computation of FSIs uses mean speed to represent overall traffic flow conditions. This approach is applicable when speed variability among vehicles is low. Minor differences between individual speeds and the average, whether above or below, generally have a minimal effect, as shown by the green curve in Figure 2-14.

However, if a group of drivers consistently travel well above the average speed and exceed the speed limit, the mean speed may not fully reflect the impact of this behavior. The red curve in Figure 2-14 illustrates this situation.

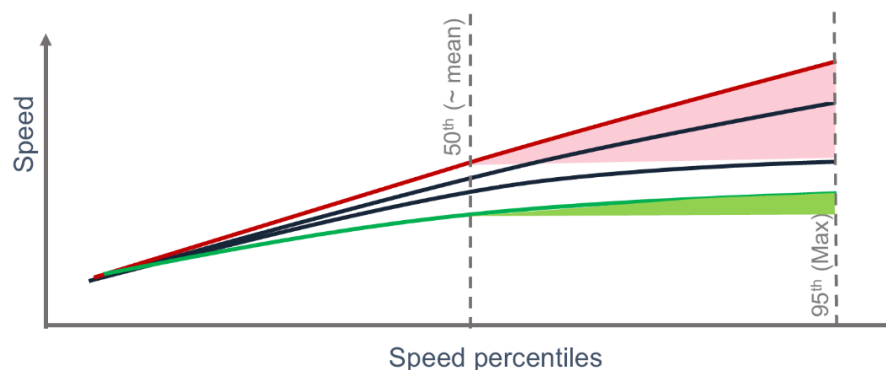


Figure 2-14 FSIs interest zones



Is there speed variability in the PHOEBE Study area?

Driver speeds vary both individually and along the corridor. Figure 2-15 displays speed variability data from road B4114 in the West Midlands. Four sites were selected for analysis based on road characteristics. Site 1 (S1) has low speed variability across all ranges. Site 2 (S2) shows consistently high variability. Sites 3 (S3) and 4 (S4) also have high variability, with S3 at lower speeds and S4 at higher speeds.

Analyzing the difference between the 50th and 95th percentiles, we can also demonstrate the high variability in speed of the exemplified corridor. S1 presented a difference of 4.45m/s ~ 9.97mph, while S2 the difference calculated is 6.00m/s ~ 13.44mph., S3 and S4 show even higher values, with S3 difference equal to 7.58m/s ~ 16.99mph and S4 to 13.04m/s ~ 29.20mph.

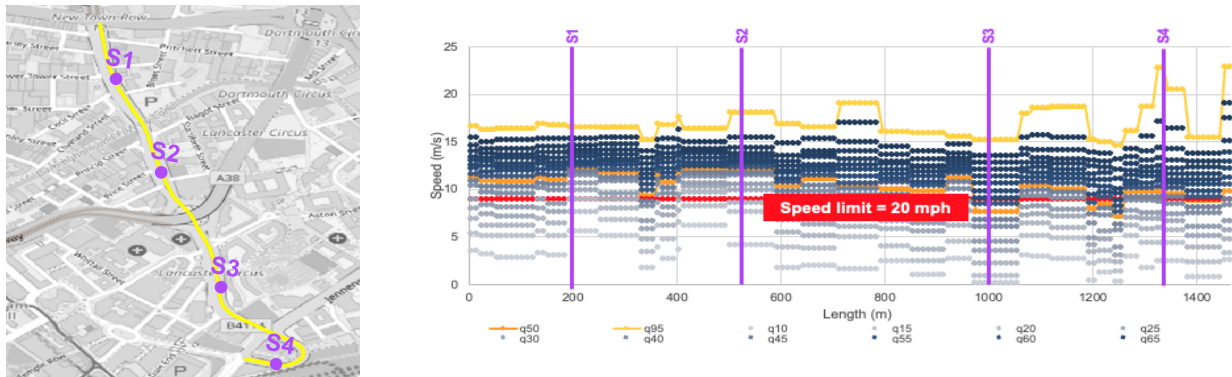


Figure 2-15 Speed variability in the B4114 Corridor – WM

Another illustrative example comes from Panepistimiou Avenue in Athens. As with the West Midlands case, four sites were selected for evaluation (see Figure 2-16). These sites were chosen to represent a range of speed variability conditions: S1 exhibited low variability, S2 displayed high variability, S3 showed low variability at higher speeds, and S4 concentrated around lower speed ranges. Examining the difference between the 95th and 50th percentile speeds, the Athens corridor demonstrated more modest variability compared to the B4114. Specifically, S1 recorded a difference of 7.44 km/h, S2 10.61 km/h, S3 6.21 km/h, and S4 5.08 km/h.

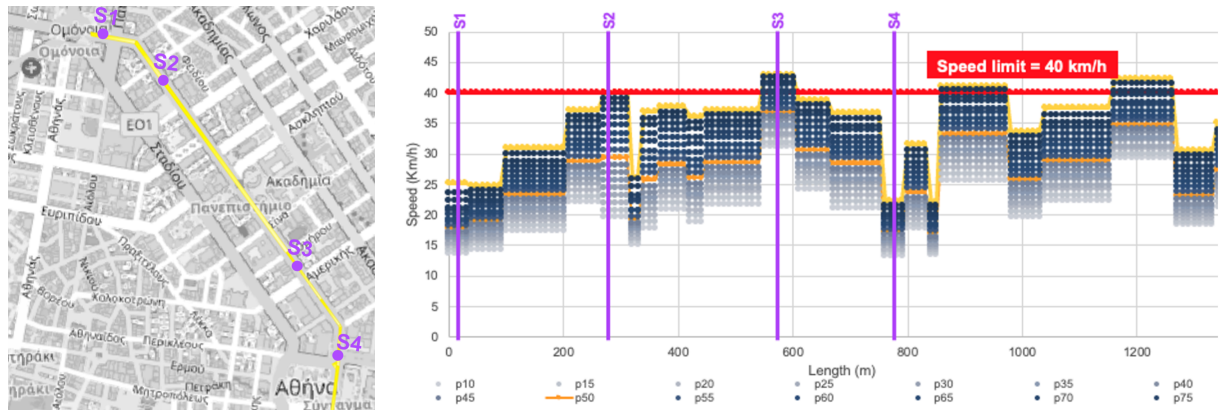


Figure 2-16 Speed variability in the Panepistimiou Avenue - Athens

Upon reviewing the charts and analyzing the study area, several insights emerge:

- Road design and characteristics have a significant impact on speed variability and the prevalence of speeding. In the Athens corridor, both speed variability and instances of speeding appear notably lower, likely a result of high traffic volumes and the presence of frequent signalized intersections that naturally curb excessive speeds. By contrast, the B4114 corridor allows for smoother and less interrupted travel, due to features such as service roads and intersections designed as merge and diverge lanes, which encourage higher speed variability.
- Ultimately, speeding leads to a more unstable and unpredictable speed profile within a corridor, as reflected in the section charts and analysis.

### Practical implications of the new FSI calibration. Factors

The baseline FSI calculation aligns with historical data, keeping total fatalities and serious injuries (FSIs) unchanged. The model assigns actual crashes to the highest-risk sections, maximizing intervention impact. With updated calibration factors, fatality allocation considers speed variability—areas with greater variation and risk (high CVs) receive more FSIs. This targets resources to higher-risk zones for maximum benefit.

After interventions, if risk drops and calibration factors remain stable, FSIs decrease, showing improved safety. The following equations illustrate calculations used in both before and after for vehicle occupant run-off crashes applied in the PHOEBE project.

$$FSIs_{VO_{RO-D-B/A(i)}} = SRS_{RO-D-B/A(i)} \times a(AADT_{NON-MC-B/A(i)})^b \times CF_{VO_{RO-D}} \times 365 / 10^9 \times CF_{Sv-B/A(i)} \times CF_{Beh-A(i)}$$

Where,

$FSIs_{VO_{RO-D-B/A(i)}}$  = number of fatalities and severe injuries in the network calculated for the before and the after scenario for segment i

$SRS_{RO-D-B/A(i)}$  = Star Rating Scores representing the risk of run of crashes for vehicle occupants calculated for the before and the after scenarios for segment (i)

a and b = AADT multiplier and AADT power, respectively

$AADT_{NON-MC-B/A(i)}$  = The AADT excluding motorcycles for the before and after scenarios in the segment (i)

$CF_{VO_{RO-D}}$  = Calibration factors based on historical data for the Run of crashes in the network

$CF_{Beh-A(i)}$  = Calibration factors to account for crashes due to the behaviors under study in the after scenarios for segment (i)

The new baseline calibration factors should not change the total number of crashes; the average calibration factor across the network must remain 1. Only the speed-related calibration factor will be used in this deliverable.

### Calculation procedure of speeding risk factors

The aim is to address speed inconsistency and apply penalties in areas where drivers surpass speed limits. This approach assumes that crashes are more frequent in zones with greater speed variability and that speed variability may serve as an indicator of speeding behavior.

There are multiple methods for calculating speed variability. Three approaches have been evaluated:

- Coefficient of Variation (CV)
- 95th to 50th percentiles





### Standard Deviation (STD)

These metrics were tested using telematics data for Athens and the West Midlands.

Project preference metrics are derived from standard simulation outputs, facilitating replicability and reducing the data processing required for integration. Among these, the Coefficient of Variation (CV) and Standard Deviation (Std Dev) align with these goals. However, the 95th–50th percentile metric offers a closer representation of theoretical considerations regarding the influence of drivers exceeding average traffic speeds.

The chart presented in Figure 2-17 compares the CV and Std Dev metrics with the 95th–50th percentile metric, indicating that discrepancies are minimized when evaluating Std Dev alongside the 95th–50th measure. Consequently, Std Dev was selected as the primary speed variability metric in the PHOEBE framework.

Despite this decision, it remains uncertain which metric most accurately captures the effects of speeding drivers. Further research is warranted to elucidate the relationship between speed variability and road safety outcomes.

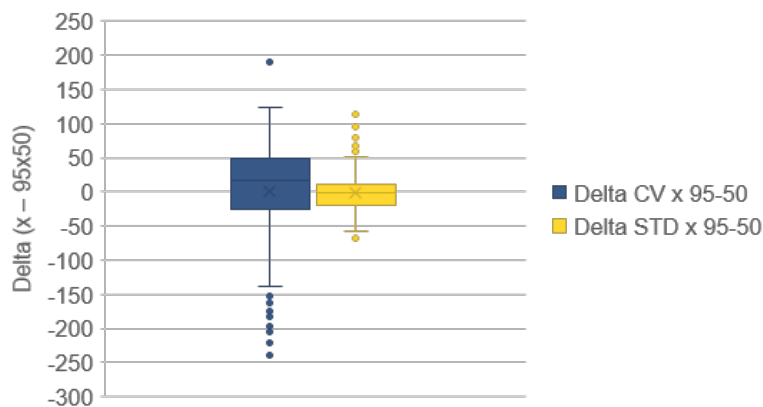


Figure 2-17 Testing of speed variability coefficients - Athens example

### 2.3.4. Risk Assessment Model Testing

Testing changes to risk factors is essential to understanding their impact on model performance. The testing process focuses on specific crash types that are more complex, particularly pedestrian and bicyclist crashes at crossings and intersections.

Testing procedure:

1) Establishing testing scenarios: Establishing testing scenarios is essential for evaluating the impact of changes or the functionality of systems like risk models. These scenarios create a structured environment to systematically assess how specific changes or variables influence outcomes, helping to isolate and identify the effects of individual factors.

In these testing scenarios, specific attributes are held at standard values while the attributes being tested are varied according to a predefined testing plan. This strategy ensures that tests can be repeated under identical conditions, making the results more reliable and reproducible. Such consistency is critical for validating findings and drawing robust conclusions.

The image on the right presents the testing scenarios for pedestrian crossings on the inspected road and side road.



2) Evaluating Expected Impact: The risk assessment models must incorporate the latest knowledge and best practices from the road safety community, including initiatives such as forgiving roads and the Safe System Approach. As a result, the expected impact is evaluated from two key perspectives:

Model Performance: How is the model anticipated to perform in assessing risk?

Impactful Attributes: Which attributes are likely to have the most significant influence on the model's calculations?

Figure 2-18 illustrates the expected risk at pedestrian crossing points in intersections where merge or diverge lanes are present.

Testing changes to risk factors is essential to understanding their impact on model performance. The testing process focuses on specific crash types that are more complex, particularly pedestrian and bicyclist crashes at crossings and intersections.

**3) Testing and comparing results:** The figures below illustrate the testing scenarios and results of the newly developed risk factors and Star Rating bands, applied to a well-designed road with no intersections and a signalized pedestrian crossing. These charts provide a clearer understanding of how the end user results (Star Rating bands) align with road safety objectives regarding speeds, flows, and the number of lanes. Figure 2-18 shows examples of the star rating bands testing.

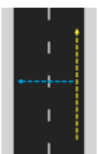
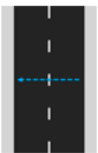
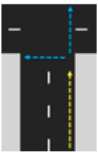
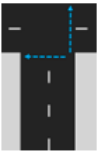
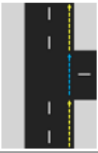
| Test #                                                                                                     | Intersection                                                                                     | Flows                                             | Crash types |                           |                        |
|------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------------|-------------|---------------------------|------------------------|
|                                                                                                            |                                                                                                  |                                                   | PED Along   | PED Crossing through road | PED Crossing side road |
|  Pedestrian Test 1 (P1)  | No intersection<br>AJ/AK/AL/AM = 12/1/7/3                                                        | Along and crossing flow:<br>BM/BN/BO = 2/2/2      | ✓           | ✓                         | ✗                      |
|  Pedestrian Test 3 (P3) | No intersection<br>AJ/AK/AL/AM = 12/1/7/3                                                        | Crossing flow only:<br>BM/BN/BO = 2/1/1           | ✗           | ✓                         | ✗                      |
|  Pedestrian Test 4 (P4) | Intersection present (Type varies)<br>Variable side road flow<br>Intersection quality = adequate | Along and crossing flow:<br>BM/BN/BO/BP = 2/2/2/2 | ✓           | ✓                         | ✓                      |
|  Pedestrian Test 5 (P5) | Intersection present (Type varies)<br>Variable side road flow<br>Intersection quality = adequate | Crossing flow only:<br>BM/BN/BO = 2/1/1           | ✗           | ✓                         | ✓                      |
|  Pedestrian Test 6 (P6) | Intersection present (Type varies)<br>Variable side road flow<br>Intersection quality = adequate | Along flow only:<br>BM/BN/BO = 1/2/2              | ✓           | ✗                         | ✓                      |

Figure 2-18 Attribute combination to test impact on pedestrian risk

The complete testing results can be found in the documents:



### Pedestrian and Bicyclist Star Rating Model Review - 1 Speed, External Flow, and Star Rating Bands

### Pedestrian and Bicyclist Star Rating Model Review - 2 Facility Risk Factors for Pedestrian and Bicycle Along Crash Types

### Pedestrian Star Rating Model Review - 3 Facility Risk Factors for Pedestrian Crossing

NEW SR BANDS: Good standard road - signalised crossing (crossing flow only)

| PEDESTRIAN |         | Lanes |       |       |       |       |       |       |       |       |       | Lanes |       |       |       |       |       |       |       |       |       |
|------------|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| speed      | cc AADT | 2000  | 4000  | 6000  | 8000  | 10000 | 12000 | 14000 | 16000 | 18000 | 20000 | 4000  | 8000  | 12000 | 16000 | 20000 | 24000 | 28000 | 32000 | 36000 | 40000 |
| 110 10km/h | 0.02    | 0.03  | 0.04  | 0.05  | 0.06  | 0.07  | 0.08  | 0.08  | 0.09  | 0.10  | 0.10  | 0.04  | 0.07  | 0.09  | 0.11  | 0.12  | 0.14  | 0.15  | 0.17  | 0.18  | 0.20  |
| 120 20km/h | 0.06    | 0.09  | 0.12  | 0.15  | 0.17  | 0.19  | 0.21  | 0.23  | 0.25  | 0.27  | 0.27  | 0.12  | 0.19  | 0.24  | 0.29  | 0.34  | 0.38  | 0.42  | 0.46  | 0.50  | 0.53  |
| 1 30km/h   | 0.16    | 0.25  | 0.32  | 0.39  | 0.45  | 0.51  | 0.56  | 0.62  | 0.67  | 0.71  | 0.71  | 0.32  | 0.50  | 0.65  | 0.79  | 0.90  | 1.02  | 1.12  | 1.23  | 1.33  | 1.43  |
| 3 40km/h   | 0.41    | 0.63  | 0.82  | 0.99  | 1.14  | 1.29  | 1.41  | 1.56  | 1.69  | 1.80  | 1.80  | 0.82  | 1.26  | 1.63  | 1.98  | 2.28  | 2.57  | 2.83  | 3.11  | 3.37  | 3.60  |
| 5 50km/h   | 0.91    | 1.41  | 1.82  | 2.22  | 2.55  | 2.87  | 3.16  | 3.47  | 3.77  | 4.03  | 4.03  | 1.82  | 2.82  | 3.64  | 4.43  | 5.10  | 5.75  | 6.32  | 6.95  | 7.53  | 8.06  |
| 7 60km/h   | 1.65    | 2.55  | 3.29  | 4.01  | 4.61  | 5.19  | 5.71  | 6.28  | 6.81  | 7.28  | 7.28  | 3.29  | 5.09  | 6.59  | 8.02  | 9.22  | 10.39 | 11.42 | 12.56 | 13.61 | 14.56 |
| 9 70km/h   | 2.39    | 3.60  | 4.65  | 5.66  | 6.51  | 7.34  | 8.07  | 8.87  | 9.62  | 10.28 | 10.28 | 4.65  | 7.20  | 9.31  | 11.32 | 13.03 | 14.67 | 16.13 | 17.74 | 19.23 | 20.57 |
| 11 80km/h  | 2.78    | 4.23  | 5.47  | 6.66  | 7.66  | 8.62  | 9.48  | 10.43 | 11.31 | 12.09 | 12.09 | 5.47  | 8.46  | 10.94 | 13.31 | 15.32 | 17.25 | 18.96 | 20.86 | 22.61 | 24.18 |
| 13 90km/h  | 8.76    | 13.55 | 17.52 | 21.32 | 24.53 | 27.63 | 30.37 | 33.41 | 36.22 | 38.73 | 38.73 | 17.52 | 27.10 | 35.05 | 42.64 | 49.07 | 55.26 | 60.75 | 66.82 | 72.43 | 77.46 |
| 15 100km/h | 8.98    | 13.89 | 17.96 | 21.86 | 25.15 | 28.32 | 31.14 | 34.25 | 37.13 | 39.70 | 39.70 | 17.96 | 27.79 | 35.93 | 43.71 | 50.30 | 56.65 | 62.28 | 68.51 | 74.26 | 79.41 |
| 17 110km/h | 9.07    | 14.02 | 18.13 | 22.06 | 25.38 | 28.59 | 31.43 | 34.57 | 37.47 | 40.07 | 40.07 | 18.13 | 28.04 | 36.26 | 44.12 | 50.76 | 57.17 | 62.85 | 69.14 | 74.94 | 80.13 |
| 19 120km/h | 9.10    | 14.07 | 18.19 | 22.13 | 25.47 | 28.68 | 31.53 | 34.68 | 37.59 | 40.20 | 40.20 | 18.19 | 28.13 | 36.38 | 44.26 | 50.93 | 57.36 | 63.06 | 69.37 | 75.19 | 80.40 |
| 21 130km/h | 9.11    | 14.08 | 18.21 | 22.16 | 25.50 | 28.72 | 31.57 | 34.73 | 37.64 | 40.25 | 40.25 | 18.21 | 28.17 | 36.43 | 44.32 | 51.00 | 57.43 | 63.14 | 69.45 | 75.28 | 80.50 |
| 23 140km/h | 9.11    | 14.09 | 18.22 | 22.17 | 25.51 | 28.73 | 31.58 | 34.74 | 37.66 | 40.27 | 40.27 | 18.22 | 28.18 | 36.44 | 44.34 | 51.02 | 57.46 | 63.16 | 69.48 | 75.31 | 80.53 |
| 25 150km/h | 9.11    | 14.09 | 18.22 | 22.17 | 25.51 | 28.73 | 31.59 | 34.75 | 37.66 | 40.27 | 40.27 | 18.22 | 28.19 | 36.45 | 44.34 | 51.03 | 57.46 | 63.17 | 69.49 | 75.32 | 80.55 |

|            |         | Lanes |       |       |       |       |       |        |        |        |        | Lanes |       |       |       |        |        |        |        |        |        |
|------------|---------|-------|-------|-------|-------|-------|-------|--------|--------|--------|--------|-------|-------|-------|-------|--------|--------|--------|--------|--------|--------|
| speed      | cc AADT | 6000  | 12000 | 18000 | 24000 | 30000 | 36000 | 42000  | 48000  | 54000  | 60000  | 8000  | 16000 | 24000 | 32000 | 40000  | 48000  | 56000  | 64000  | 72000  | 80000  |
| 110 10km/h | 0.07    | 0.10  | 0.13  | 0.16  | 0.19  | 0.21  | 0.23  | 0.25   | 0.27   | 0.29   | 0.29   | 0.09  | 0.14  | 0.18  | 0.22  | 0.25   | 0.28   | 0.31   | 0.34   | 0.37   | 0.39   |
| 120 20km/h | 0.18    | 0.28  | 0.36  | 0.44  | 0.51  | 0.57  | 0.63  | 0.69   | 0.75   | 0.80   | 0.80   | 0.24  | 0.37  | 0.48  | 0.59  | 0.68   | 0.76   | 0.84   | 0.92   | 1.00   | 1.07   |
| 1 30km/h   | 0.48    | 0.75  | 0.97  | 1.18  | 1.36  | 1.53  | 1.68  | 1.85   | 2.00   | 2.14   | 2.14   | 0.65  | 1.00  | 1.29  | 1.57  | 1.81   | 2.04   | 2.24   | 2.46   | 2.67   | 2.85   |
| 3 40km/h   | 1.22    | 1.89  | 2.45  | 2.98  | 3.43  | 3.86  | 4.24  | 4.67   | 5.06   | 5.41   | 5.41   | 1.63  | 2.52  | 3.26  | 3.97  | 4.57   | 5.14   | 5.65   | 6.22   | 6.74   | 7.21   |
| 5 50km/h   | 2.73    | 4.23  | 5.47  | 6.65  | 7.65  | 8.62  | 9.48  | 10.42  | 11.30  | 12.08  | 12.08  | 3.64  | 5.64  | 7.29  | 8.87  | 10.21  | 11.49  | 12.64  | 13.90  | 15.07  | 16.11  |
| 7 60km/h   | 4.94    | 7.64  | 9.88  | 12.02 | 13.83 | 15.58 | 17.13 | 18.84  | 20.42  | 21.84  | 21.84  | 6.59  | 10.19 | 13.18 | 16.03 | 18.45  | 20.77  | 22.84  | 25.12  | 27.23  | 29.12  |
| 9 70km/h   | 6.98    | 10.80 | 13.96 | 16.98 | 19.54 | 22.01 | 24.20 | 26.62  | 28.85  | 30.85  | 30.85  | 9.31  | 14.39 | 18.61 | 22.65 | 26.06  | 29.35  | 32.26  | 35.49  | 38.47  | 41.14  |
| 11 80km/h  | 8.21    | 12.69 | 16.41 | 19.97 | 22.98 | 25.87 | 28.45 | 31.29  | 33.92  | 36.27  | 36.27  | 10.94 | 16.92 | 21.88 | 26.62 | 30.63  | 34.50  | 37.93  | 41.72  | 45.22  | 48.36  |
| 13 90km/h  | 26.29   | 40.66 | 52.57 | 63.96 | 73.60 | 82.89 | 91.12 | 100.24 | 108.65 | 116.18 | 116.18 | 35.05 | 54.21 | 70.10 | 85.28 | 98.13  | 110.52 | 121.50 | 133.65 | 144.87 | 154.91 |
| 15 100km/h | 26.95   | 41.68 | 53.89 | 65.57 | 75.45 | 84.97 | 93.42 | 102.76 | 111.38 | 119.11 | 119.11 | 35.93 | 55.57 | 71.86 | 87.43 | 100.60 | 113.30 | 124.56 | 137.01 | 148.51 | 158.81 |
| 17 110km/h | 27.20   | 42.06 | 54.39 | 66.17 | 76.15 | 85.76 | 94.28 | 103.70 | 112.41 | 120.20 | 120.20 | 36.26 | 56.08 | 72.52 | 88.23 | 101.53 | 114.34 | 125.70 | 138.27 | 149.88 | 160.27 |
| 19 120km/h | 27.29   | 42.20 | 54.57 | 66.40 | 76.40 | 86.04 | 94.59 | 104.05 | 112.78 | 120.60 | 120.60 | 36.38 | 56.27 | 72.76 | 88.53 | 101.87 | 114.72 | 126.12 | 138.73 | 150.38 | 160.80 |
| 21 130km/h | 27.32   | 42.25 | 54.64 | 66.48 | 76.49 | 86.15 | 94.71 | 104.18 | 112.92 | 120.75 | 120.75 | 36.43 | 56.34 | 72.85 | 88.63 | 101.99 | 114.86 | 126.27 | 138.90 | 150.56 | 161.00 |
| 23 140km/h | 27.33   | 42.27 | 54.66 | 66.50 | 76.53 | 86.18 | 94.75 | 104.22 | 112.97 | 120.80 | 120.80 | 36.44 | 56.36 | 72.88 | 88.67 | 102.03 | 114.91 | 126.33 | 138.96 | 150.62 | 161.07 |
| 25 150km/h | 27.34   | 42.28 | 54.67 | 66.52 | 76.54 | 86.20 | 94.76 | 104.24 | 112.98 | 120.82 | 120.82 | 36.45 | 56.37 | 72.89 | 88.69 | 102.05 | 114.93 | 126.35 | 138.98 | 150.65 | 161.09 |

Figure 2-18 New SR enhanced bands testing

### 2.3.5. Risk Assessment Model Validation

The PHOEBE Risk Assessment Feedback Form was developed to standardize the collection of expert evaluations across the project's use cases—Athens, Valencia, and West Midlands. It supports the validation of updates made to iRAP's Star Rating and Fatal and Serious Injury (FSI) Estimation models, which have been enhanced to improve predictive safety capabilities for urban road networks, particularly for vulnerable road users. The form begins with a section titled "About You," where respondents provide their name, contact email, and indicate their familiarity with the area under analysis (e.g., unfamiliar, familiar, or very familiar). This is followed by an "About the Assessments" section, which explains the model updates and their alignment with PHOEBE principles, including improved modeling of shared paths and mid-block crossings for bicyclists.

The core of the form consists of structured questions designed to capture the correspondence between model outputs and local expectations. For each road user group—car occupants, motorcyclists, pedestrians, and bicyclists—respondents rate the alignment of risk results using a five-point scale from "very low" to "very high." They are also asked to identify specific locations where the model's risk estimates may require revision, providing details such as street names or coordinates. The form includes dedicated subsections for crash-type assessments, such as "Pedestrians – Crossing Risk" and "Bicyclists – Intersection Risk," where respondents compare numeric Star Rating Scores across locations. These detailed inputs help calibrate the models and ensure that enhancements reflect real-world conditions. The form concludes with a section on FSI estimations.

Several respondents in the PHOEBE feedback form rated the risk correspondence for different road user groups as high or very high, indicating strong alignment between the model outputs and their expectations in specific contexts. For car occupants, four participants expressed high confidence in the results. However,



they also flagged specific segments—such as AIM-id 480.564 and Bulevar Periférico Norte—for inconsistent ratings or overlooked risk factors like poor visibility and pedestrian interaction. Similarly, motorcyclist risk ratings received five high or very high responses, with comments suggesting that motorcycle vulnerability should be more prominently reflected, especially in shared traffic environments.

For pedestrians, three respondents gave high ratings, noting that while some sidewalk conditions were well captured, crossing risks on high-speed roads were underestimated. In the case of bicyclists, four participants rated the model output as highly aligned with their expectations, but still pointed out discrepancies in infrastructure representation. For example, Calle de Ramón Llull was flagged for inconsistent ratings across directions despite being a two-way bike lane, and several streets in Athens were rated higher than warranted based on local traffic conditions. These insights helped to review the results and realignment of the data or models for the highlighted issues.

More details on the form and feedback can be found in the A.6 Risk assessment validation form resultsA.6 Risk assessment validation form results

### 2.3.6. Risk Assessment Model Results per Use Cases

The enhancements to the model provide comprehensive, static risk assessment results, though full integration with other modelling components is still not completed at this stage. For each use case, an interactive data dashboard was created and shared with the respective case leaders, offering a clear visualization and deeper insights into the assessment outcomes. These dashboards are accessible via the links provided below.

- [Athens Risk Assessment Dashboard](#)
- [Valencia Risk Assessment Dashboard](#)
- [West Midlands Risk Assessment Dashboard](#)

## 2.4. Traffic Simulation Model

This section covers various aspects of traffic simulation models enhancements, focusing on human behaviours and technical developments.

It begins with an overview of the enhancements made to the road safety assessment component, including model calibration and model enhancement. It delves into specific human behaviours that have been added to the traffic simulation software to enable realistic safety-critical interactions. These behaviours include speeding, red light violations for vehicles and pedestrians, as well as pedestrians crossing in non-designated areas.

On the model calibration, the chapter details the improvements made to the Aimsun simulation networks for the PHOEBE use cases in Athens, Valencia, and the West Midlands. Each city's model calibration process is described, including the integration of pedestrians, motorized vehicles, and interventions.

### 2.4.1. Traffic Simulation Model Behavioural APIs

In order to enable realistic safety-critical interactions, some non-compliant behaviours (NCBs) have been added to the traffic simulation software. For the PHOEBE use cases and goals, these are:

- Speeding
- Red light violation for vehicles
- Pedestrians crossing in non-designated areas
- Red light violation for pedestrians



All of them require that the simulation agents, either vehicles or pedestrians, perform some actions against the rules of traffic. The NCBs had to be explicitly implemented in the Aimsun Next software, as they are not standard behaviours of agents. This speeding behaviour already existed as an option in the simulation. Nevertheless, it had to be fine-tuned to fit the PHOEBE use case.

In all cases, these behaviours have been modelled by using an API that enables the triggering of the behaviours on demand, given some input parameters (such as pedestrian and vehicle IDs that will perform the violations, as well as the locations – section/crossing IDs, where the NCBs will occur)

### 2.4.1.1. Speeding

Speeding is the behaviour of driving above the road/street speed limit. Since this is a prevalent behaviour in many places of the world, it is a feature already implemented in Aimsun's simulation tool. It is implemented as the speed limit acceptance parameter, see Aimsun online manual: *Vehicle Types - Aimsun Next Users Manual* (Aimsun, 2025).

This is a parameter that can be interpreted as a multiplier of the speed limit, so if it is smaller than 1, the vehicle will never reach the speed limit, if it is 1, the vehicle will travel (if possible) at the speed limit, and if is greater than 1, for instance 1.2 will the vehicle will try to travel at 20% faster than the speed limit, again if possible.

This is one of the three main factors that determine the speed in the simulation:

1. Speed limit \* speed limit acceptance
2. Maximum desired speed (a combination of the maximum speed of the vehicles + what the driver is willing to drive), see: *Vehicle Types - Aimsun Next Users Manual* (Aimsun, 2025).
3. Car following model: *Modeling Vehicle Movement - Aimsun Next Users Manual* (Aimsun, 2025).

For an urban environment like the one in PHOEBE, the main factors are 1 and 3. The implementation of NCB is on the first point, we let drivers go potentially faster. Nonetheless, they are still limited by their acceleration, so they take some time to reach the final speed and are constrained by the surrounding traffic. If the gap to the preceding vehicle is small enough, the vehicle will be forced to reduce its speed even if it wants to speed.

#### Technical development

The logic for triggering vehicles to travel significantly faster than the speed limit is implemented in a Python API for the Aimsun microsimulation platform. A high-level description is provided on the following slide with a flowchart detailing the logic.

The key points are that the human behavioural models need traffic and human information to assess the probability of speed. Details on these can be found in the human behavioural section. To explain how this is implemented, it is important to point out that there are two types of variables: those that are (mostly) already available in the simulation and those that are not. In the first category falls everything that is strongly related to traffic attributes, even if it needs significant processing to obtain, is available in the simulation, and there is no need to input it. In the second category, typically human-related parameters are not available in the simulation and need to be externally input. Following a list of parameters for use-cases (in bold ones that need external input):

- High traffic,
- speed limit,
- speed enforcement device,
- gender,



- past behaviour of speeding, and
- SVO

#### The API architecture

Upon the API initialization, it takes input parameters from a YAML file, so they are not hardcoded into the code. This way, it can be more easily transferred to other use cases.

Then it initializes the information it needs at a section level, which is:

- Speed camera
- High/low traffic variable

The simulation process unfolds in a structured sequence, beginning with an initialization phase where time is segmented into multiple discrete intervals. At each interval, specific actions are performed for every vehicle entering the network. This approach ensures that each vehicle is assigned parameter values not inherently available in the default simulation tool.

As vehicles transition from one section of the network to another, the system identifies these moments to activate or deactivate speeding behaviors accordingly. Periodically, as new traffic data becomes available, the simulation adjusts the high or low traffic variable to reflect current conditions.

Upon completion of the simulation, all results are systematically postprocessed and archived to enable thorough analysis at a later stage. Figure 2-19 presents the API structure.

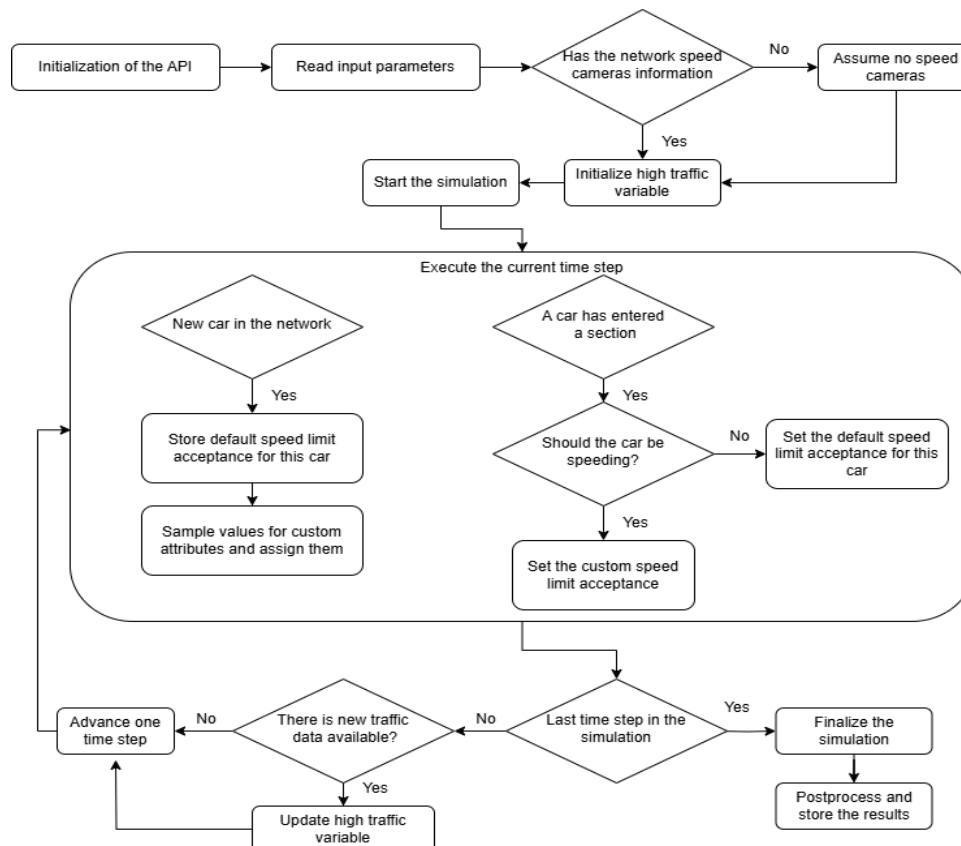


Figure 2-19 Speeding API architecture



### 2.4.1.2. Red light violation for micromobility

For the Valencia use case, it is necessary to have micromobility vehicles skip red lights at given locations. Since this was not a feature available on the software, the following steps were taken.

- 1) A new function has been added to the software back end to enable vehicles to skip a red light.
- 2) A new function has been exposed to the API, so that this behaviour can be triggered on demand.
- 3) An API has been coded that triggers these behaviours based on the requirements set by the partners for the Valencia network.

API workflow is a highly customized development. It requires some manual input to work.

- API takes manual input on the locations it needs to trigger the behaviours
- The potential crossing vehicle paths need to be coded as subpaths into the software and entered manually. That way, the API can keep track of potential conflict vehicles and compute the time gap until the conflict point.
- The API automatically assigns to the micromobility users a set of parameters given the probabilistic distributions: age, social value orientation, past behaviour of red-light violation, and past behaviour of running out of the bicycle lane.
- It also assigns automatically to the crossings if they are wide or narrow, given the geometry. It also updates the traffic attribute considering the last available data.
- Every time a micromobility vehicle reaches an intersection coded for violation, it checks whether it should violate or not the red light at each simulation step. This is to update to check the time gap of incoming vehicles.
- Finally, all the sampled values for human behaviour parameters and the activations of red-light violations are saved into a file for posterior analysis.

#### API architecture

Implementation of the Red-Light Violation (RLV) is more complex than speeding, mainly due to 2 factors:

- Isn't behaviour common enough that it was already coded in the software
- There is a need to check for incoming traffic, so there is a high enough chance of a successful crossing for that to happen, as determined by the human behaviour modelling.

The high-level architecture of the API is described as follows, accompanied by a flowchart to visualize the whole process.

The API takes 2 input files to have the external information needed to operate:

- Behavioural parameters for RLV violation
- Information (Aimsun's ID) on the intersections where RLV should be triggered and the approach path to the points of conflict.

With the information of the intersections of interest, the API automatically gathers the required information on the approach routes, i.e., the distance of each network object involved in the conflict zone, and some other parameters are initialized.

The following simulation is started on a time-discrete basis, i.e., by time steps. At each time step, the following is checked:

- Check if a vehicle has entered one of the monitored paths that lead to a conflict point. If that is the case, start tracking the vehicle and add it to a list of monitored vehicles.





### 3.2 – Finalized models/simulation environments, methodology factsheets and users support materials

- Check if a previously monitored car has already traveled past the conflict point. If so, stop tracking the vehicle and remove it from the list of monitored vehicles.
- If a new micromobility vehicle has entered the network, add the behavioural attributes for the RLV behaviour.
- Check if there is any micromobility vehicle that fulfils the following:
  - In a section that leads to an RLV-enabled intersection
  - Less than 10m from the end of the section (traffic light)
  - The traffic light is currently not green
- If all the previous conditions are proper, then this is a candidate to perform RLV, so we proceed to gather all the information needed.
  - Retrieve vehicle behavioural parameters.
  - Retrieve high/low traffic status.
  - Check if there is any close vehicle (time gap < 6s)
- With that, a probability of skipping RLV is computed. If that is above the set threshold, the user's violation is enabled. If not, the process will be repeated in the next time step
- After the time step has been computed, new traffic statistics might be available (they are gathered at user-defined intervals of typically 10-15 minutes). If that is the case, update the high/low traffic variable
- Repeat the previous until the simulation is finished
- Retrieve and store information on RLV activations and micromobility users' parameters into a file for further processing

This process is presented in Figure 2-20.

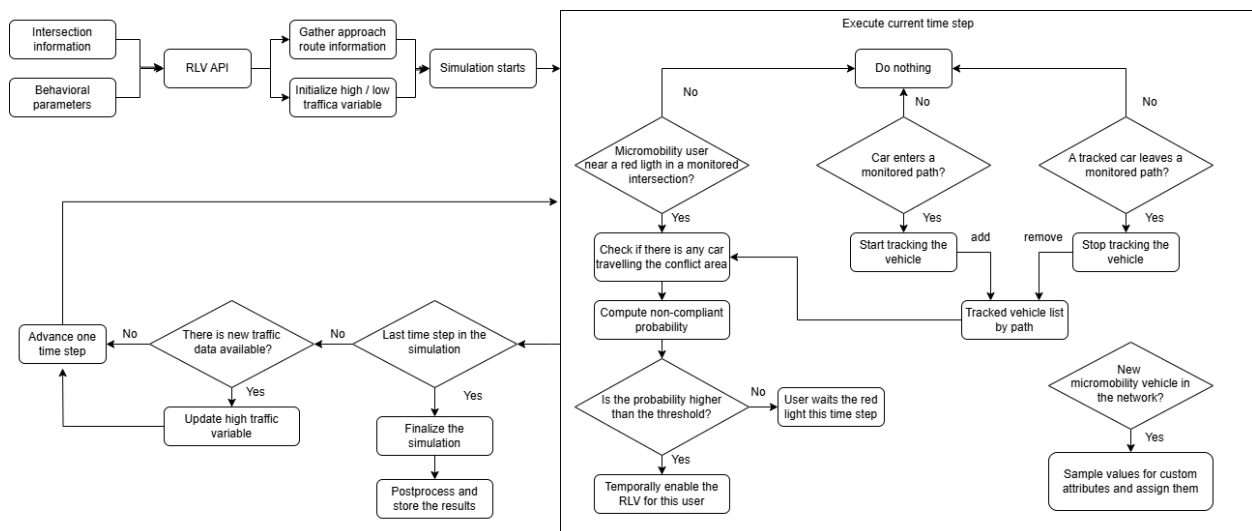


Figure 2-20 Red light violation for micromobility API architecture<sup>5</sup>

<sup>5</sup> A video demonstration of the behaviour API can be seen [here](#)



### 2.4.1.3. Red light violation for pedestrians

For the Athens use case, there is a need to model pedestrian red-light violations at pedestrian crossings. To have this functionality in the simulation environment, new functions have been added to the Aimsun Next simulation software:

- 1) The behaviour of skipping the red light for pedestrians has been added to the software
- 2) A function has been added to trigger this behaviour through the API
- 3) The API with the required PHOEBE logic has been coded

The API logic is as follows

- Upon initialisation, it gets all pedestrian crossings in the (sub)network and gets the pedestrian crossing waiting areas' coordinates.
- For all pedestrian crossings, it fetches which signal group they are, so at later stages, it is possible to determine if they have a green light or not.
- When a pedestrian enters the network, social attributes, such as age and being in a rush, are added.
- At each time step, check all pedestrians to see if they are inside a waiting area of a pedestrian crossing. Pedestrians in these areas are subject to a red light violation.
- For those inside a waiting area, check if the signal is not green. If this is the case, compute the probability of a red-light crossing. If the probability is higher than 50%, enable the noncompliant behaviour.
- Once the Red-light behaviour is activated, keep it activated for 15 seconds. This is to ensure the pedestrian can start crossing, i.e., move from its original position to a point where it has started crossing.

#### API architecture

The API is designed for seamless integration and automated operation within the traffic simulation environment. Upon initialization, it requires only the appropriate behaviour parameters to be specified. From that point, the API autonomously collects all necessary inputs, such as the width of each pedestrian crossing—including the number of lanes—the spatial boundaries of waiting areas, and real-time traffic flow data at every crossing point.

With each simulation timestep, the system systematically monitors the location of every pedestrian within the network, checking whether they have entered any of the designated pedestrian crossing waiting areas. For those pedestrians who are found within these zones, the system performs an additional assessment to verify whether the corresponding traffic light is not green. If this condition is met, the API calculates the probability of a red-light crossing event. Should this probability exceed a defined threshold, the noncompliant crossing behaviour is triggered, allowing the simulation to reflect real-world pedestrian decision-making under varied circumstances.

Once the simulation concludes, the API generates a comprehensive set of custom outputs, carefully recorded for subsequent analysis. These outputs provide valuable insights into the occurrence of red-light crossings and pedestrian behavioural patterns. The logic behind this process is illustrated in detail by a flowchart presented in the following Figure 2-21.



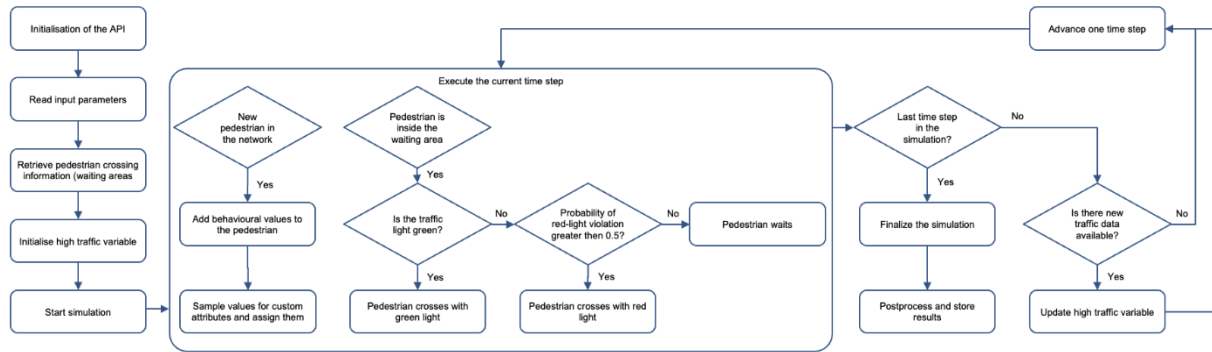


Figure 2-21 Red light violation for pedestrians API architecture<sup>6</sup>

### 2.4.1.4. Crossing outside designated areas

For the Athens use case, there is a need to have pedestrians cross at non-designated areas. While this functionality was available in Aimsun Next as an extra plug-in, it could not be triggered through the API. Thus, a new API function to trigger pedestrian crossings at any point had to be added.

The function enables the pedestrian to find a shorter path to the destination, regardless of the availability of pedestrian crossings. If possible, it will change its route to a path that crosses the sections at a suitable point for the shortest path. Still, the pedestrian checks for incoming traffic and might choose to detour or wait for some time before attempting to cross if the gap in incoming traffic is short enough to guarantee a crash. This is a realistic possibility based on observed pedestrian behaviour.

Given the nature of this behaviour, it is not possible to control in the simulation with a high level of detail without the need for very complex models that are not within the scope of PHOEBE. Thus, some simplifications had to be made, mainly that the behaviours will be activated or deactivated per pedestrian, not based on local conditions, but on the route conditions. So, a pedestrian travelling from origin A to destination B will or will not be allowed to cross outside designated areas on the whole route based on the traffic levels and width of the streets on that route at that given moment.

#### Technical development

Provide three files with the pedestrian OD pair information:

- One of the main sections IDs to be crossed for each OD pair (high/low traffic)
- One with a binary value to represent if there are any broad sections to cross
- One with a binary value to represent if there are any two-directional streets on that OD pair path

These could be automated, but given the limited scope of application in PHOEBE, it was deemed that this manual input was the most cost-efficient way to do it, as automation of this simple input would imply a heavy development on path finding, which was beyond the scope of the project.

Upon initialization, the API loads the 3 files and checks that the information they contain is correct in the formal sense. This means correct shape and OD pairs, as well as ID inputs.

Then, when a pedestrian enters the network, some behavioural parameters for that pedestrian are added.

<sup>6</sup> A video demonstration of the behaviour API can be seen [here](#).



Then we check the destination of the pedestrian and assess the probability of that pedestrian crossing outside the designated areas, considering its behaviour parameters and the OD pair characteristics. If that probability is higher than 0.5, the behaviour of crossing outside the designated areas is enabled for the whole journey. Otherwise, it will only cross in designated areas. Note that not all pedestrians who are enabled for this behaviour will be able to perform a red light violation, as they follow a different logic.

A flowchart of this process is shown in Figure 2-22.

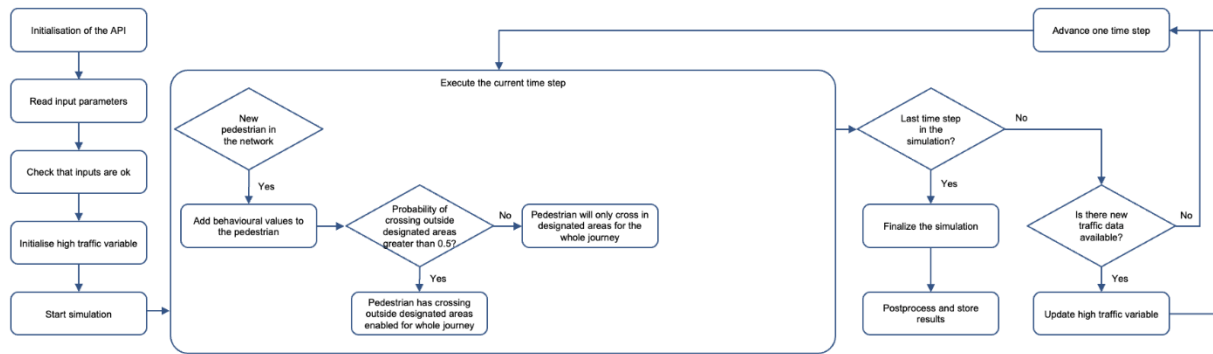


Figure 2-22 Crossing outside designated areas API architecture<sup>7</sup>

### 2.4.1.5. Other integrations needed

#### OD matrices

To integrate the traffic simulation with other project tools, we have needed to write some scripts to automate the process of exporting and importing OD matrices, as well as exporting Skim matrices. Most of these functions were already present in the Aimsun software, and the ones missing have been added for the execution of another Horizon project (**ACUMEN**) before PHOEBE has utilized them. The process includes:

- 1) Scripts to export and import OD matrices
- 2) Scripts to export skim matrices for cost, travel time, trips, and distance
- 3) Scripts to import segmented matrices

Custom scripts have been developed in order to make this process easy and automatable for all the partners in the project.

#### Other needs

To enable the execution of the PHOEBE framework, it is necessary to extract both standard and custom Aimsun outputs. Here are described the ones that have not been covered previously in this document.

- Extract the section geometries with their ID (iRAP) - Standard output
- Extract the centroid location, areas, and ID (TUM) - Standard output
- Extract the node shape (spatial coverage) and ID (iRAP) - Custom output
- Extract the whole simulation mean speed (iRAP) - Standard output
- Extract the link 85th percentile speed for the whole simulation timeframe (iRAP) - Custom output

<sup>7</sup> A video demonstration of the behaviour API can be seen [here](#).



- Extract the link hourly mean speed (iRAP) - Custom/standard, depending on the statistic interval
- Export a \*.trj file for analysis into the SSAM software (TUD) - Standard output

### 2.4.2. Traffic Simulation Models Calibrations

For all three PHOEBE use cases, significant improvements in the Aimsun simulation networks have been needed to bring them to a state suitable for the PHOEBE framework. Details are provided in the following slides. The main work has been adding VRUs into the simulation environment for all the cities, and refining and updating the networks to reflect the current state of the city. Figure 2-23 is the highlights of all the model improvements.

This section will present the description of the API structure. More on the demonstration can be found at A.7 Demonstration of behaviours inside AIMSUN Next Software.

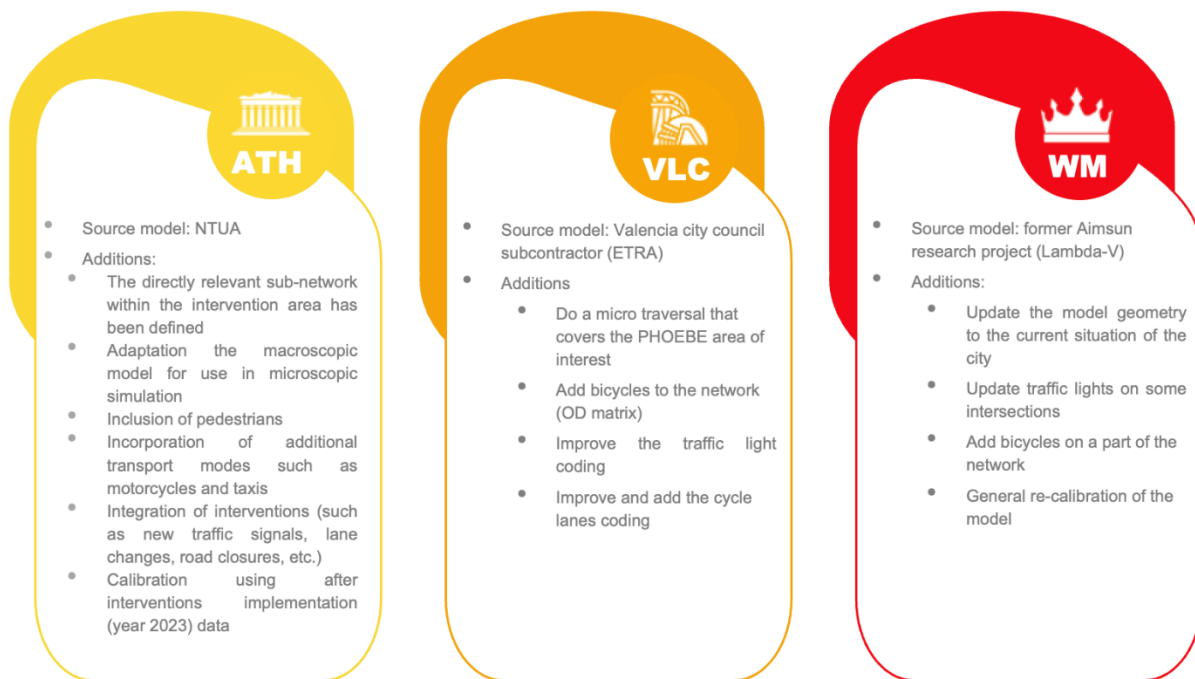


Figure 2-23 Highlights of model improvements per use cases

The Athens network, developed by the NTUA Department of Transportation Planning and Engineering, is represented using a macroscopic Aimsun-based simulation model. Within this model, a specific subnetwork was carefully delineated to correspond to the targeted intervention area. To accurately capture travel patterns, origin-destination matrices were created through traffic assignment processes carried out within the macroscopic model. The simulation network underwent targeted modifications to address the unique requirements of the intervention zone, encompassing major corridors such as Vasilissis Olgas Avenue, Panepistimiou Street, and Syntagma Square.

The subnetwork spans approximately 3 km<sup>2</sup> and includes 188 nodes and 428 road segments, with a total road length of 47 km. Figure 2-24 shows the extension of the network.

Recent Enhancements:

- Efforts have been made to adapt the existing macroscopic model for microscopic simulation.



- The model has been calibrated using 2019 data (before the integration of interventions).
- The model now incorporates additional transport modes such as motorcycles and taxis.
- Inclusion of pedestrians has been implemented.
- The model was calibrated using 2023 data after the integration of interventions.
- Interventions (such as new traffic signals, lane changes, road closures, etc.) were integrated.



Figure 2-24 AIMSUN model of the Athens study area

#### Baseline enhancements

Pedestrian integration within the simulation was meticulously approached through manual counting techniques, utilizing video footage obtained from surveillance cameras. The data collection occurred on June 11, 2020, during the morning peak hour between 8:00 and 9:00 a.m., yielding a total tally of 6,912 pedestrian movements for the simulated timeframe. To ensure accurate representation in the model, entry and exit points for pedestrians were established on each side of the crossings. These measurements informed the development of a detailed origin-destination matrix, which was incorporated into the simulation to reflect real pedestrian travel patterns.

During the morning peak hour, specifically from 8:00 to 9:00 a.m., comprehensive traffic data were gathered from the Athens Traffic Management Centre (ATMC) on select Tuesdays and Thursdays in May 2019, prior to the implementation of any interventions. These data originated from a network of nineteen detectors—cameras strategically positioned to record traffic volumes across the study area.

To ensure a thorough and representative understanding of fleet composition and traffic patterns, supplementary field measurements were conducted. These measurements spanned a week, running from Monday, November 30, to Friday, December 3, 2019, between 7:30 and 9:30 a.m., and were organized by the National Technical University of Athens (NTUA). At each network node, observers meticulously recorded the number of vehicles departing in each direction, breaking the data down into fifteen-minute intervals. This careful approach provided a detailed and nuanced depiction of traffic flows, forming a solid foundation for subsequent modeling and analysis.

The model's calibration was validated using the GEH index, which demonstrated a strong alignment between simulated and observed traffic volumes. Specifically, 85.2% of the cases—46 out of 54—had a GEH statistic below 5, while every single case achieved a value below 10. This high rate of compliance indicates a robust correspondence between the model and actual conditions. Furthermore, the simulation achieved an  $R^2$  coefficient of 0.98 through linear regression analysis, meaning that the model accurately captured 98% of the observed variations in traffic volumes. Figure 2-25 shows the assigned versus the observed flow in the network.

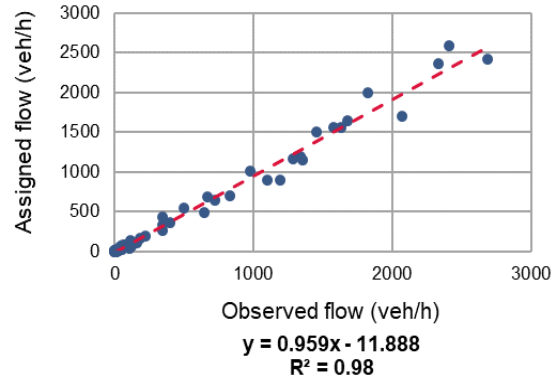


Figure 2-25 Assigned x observed flow in the baseline scenario of the Athens network

#### Interventions modelling

In June 2020, a pilot implementation of new mobility measures was carried out in the city center of Athens, including widening of sidewalks, pedestrianisation of certain streets, introduction of new exclusive bus lanes, and parking arrangements<sup>8</sup>. This allowed the project team to gather after data for the calibration of the simulation models.

During the morning peak hour, specifically between 8:00 and 9:00 a.m., comprehensive traffic data were gathered from the Athens Traffic Management Centre (ATMC) on selected Tuesdays and Thursdays in March and April 2023, following the implementation of mobility interventions. The collected information came from a network of six detectors—cameras strategically placed throughout the area to record traffic volumes accurately.

In addition to these automated counts, supplementary field measurements were undertaken to capture nuances in fleet composition and traffic dynamics. These field observations took place on Thursday, March 23, 2023, and Thursday, April 27, 2023, from 8:00 to 10:00 a.m., under the organization of the National Technical University of Athens (NTUA). At each key network node, observers carefully recorded the number of vehicles departing in every possible direction, meticulously compiling this data in fifteen-minute intervals. These combined efforts provided a thorough and detailed portrait of the evolving traffic patterns within the study area after the new mobility measures had taken effect.

Like the baseline, the results of the current model calibration underscore its robustness and accuracy. Analysis using the GEH index showed that a substantial majority—85% of cases, or 28 out of 33—achieved a GEH value below 5, while every single case maintained a value under 10. This demonstrates a consistently strong alignment between the modeled and observed traffic patterns. Furthermore, the simulation's effectiveness is reinforced by an  $R^2$  coefficient of 0.99, indicating that the model successfully accounts for 99% of the variations in actual traffic volumes.

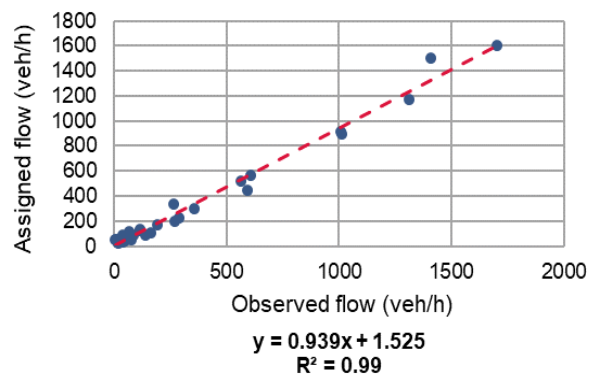


Figure 2-26 Assigned x observed flow in the intervention scenario of the Athens network

<sup>8</sup> The detail description of these interventions are described in Deliverables 4.1 and 4.2.





### 2.4.2.1. Valencia

The Valencia city council provided the original Aimsun simulation model. The model provided was macro (i.e., no vehicle dynamics) of the Valencia metropolitan area, with some minor areas with microscopic simulation (with detailed vehicle dynamics), which required significant updates to be helpful for the PHOEBE project.

The transition of the study area in Valencia for the PHOEBE project began with converting the relevant sections from a macro-level to a micro-level simulation. This process involved a deliberate traversal: the original macro model was executed, and the resulting demand and flow data were used to construct an origin-destination (OD) matrix explicitly tailored for the PHOEBE micro model.

One crucial aspect of this transformation was updating the traffic light information. In the original macro model, traffic signals at major intersections were often poorly coded, as detailed signal timing was not essential for macro-level analysis. For the micro model, however, these traffic controls required substantial refinement to reflect real-world intersection behavior accurately.

It is important to note that no micromobility demand was incorporated into the model at this stage. Additionally, the infrastructure for bicycle lanes was not represented adequately in the initial simulation. In practice, many bike lanes have been modeled as overpasses, resulting in no interactions between cyclists and cars. To address this, the bike lanes had to be integrated into the existing roadway network. This involved modifying intersections and updating the corresponding traffic light configurations to ensure that both vehicular and bicycle flows were realistically simulated.

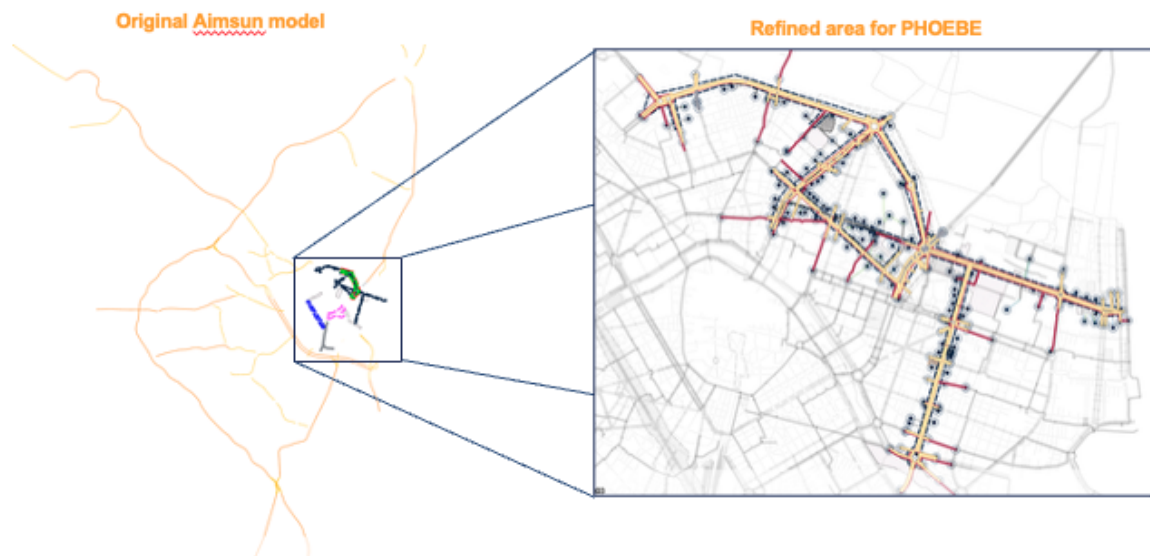


Figure 2-27 Valencia AIMSUN network

Additionally, several enhancements were performed in the models. They are:

- Inclusion and modification of intersections:** Firstly, intersections previously absent from the original framework were incorporated, ensuring a comprehensive representation of the network. Additional traffic lanes were integrated where they had not been modeled before, better mirroring the actual roadway layout. The geometry of various intersections was adjusted to align more closely with real-world conditions, thereby improving both the fidelity and performance of the simulation. Furthermore, the turning movements within existing intersections underwent meticulous refinement: more than thirty turns were systematically reviewed and updated. This process included removing turns that do not exist in reality,

correcting inaccurate turning options, and introducing missing turns that are present in the actual traffic network.



Figure 2-28 Examples of intersection adjustments in the Valencia simulation model.

- Modification of traffic signal phases:** Signal timing was updated for over 150 traffic lights, and detailed field observations were conducted at key intersections – mainly roundabouts – to analyse and adjust signal cycles, ensuring maximum alignment between the model and real-world operation.
- Update of bicycle network:** The bicycle lanes enhancements included adjusting the geometry and directionality of each lane to mirror real-world conditions. Intersections where bicycle lanes crossed or merged with motor vehicle lanes were carefully incorporated, allowing for a more realistic interaction between different traffic participants. Additionally, dedicated traffic signals for bicycle lanes were added, with signal phases designed to closely match those observed in the field, further improving the fidelity of the simulation.

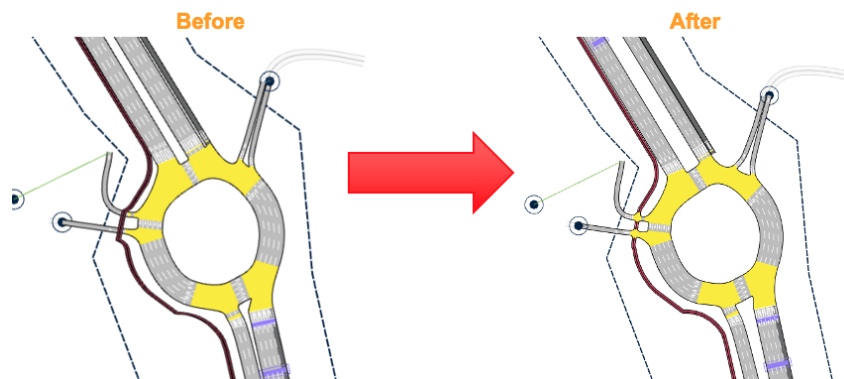


Figure 2-29 Examples of bicycle network enhancements in the Valencia simulation model.

- Adjustment of motor vehicle demand:** To ensure the model accurately represented real-world conditions, a comprehensive analysis of motorized traffic demand was conducted using data sourced from the macrosimulation model. Traffic volumes were meticulously calibrated based on detailed traffic counts collected on the main roads throughout the study area.
- Inclusion of micromobility user demand:** To accurately capture micromobility user demand, targeted fieldwork was carried out at more than ten strategically chosen intersections, each selected for its significance within the study scenario. Building on this groundwork, a tailored methodology was developed to estimate origin-destination matrices across a clearly defined set of network nodes, significantly enhancing the precision of the simulation model. These nodes were

then implemented within the model framework, allowing for the seamless integration of micromobility demand data and providing a more realistic representation of actual travel patterns.

When the baseline network was satisfactorily calibrated, the interventions that represent the testing scenarios were incorporated<sup>9</sup>. The Valencia scenarios are hypothetical, and therefore, there is no data for after calibration.

#### 2.4.2.2. West Midlands

The West Midlands model consists of two separate simulation models: Aimsun 1 and Aimsun 2 (see Figure 2-30). Aimsun 1 encompasses the city centre and extends toward the airport, following the alignment of the A45. In contrast, Aimsun 2 focuses on the Edgbaston area, situated south of the city centre.

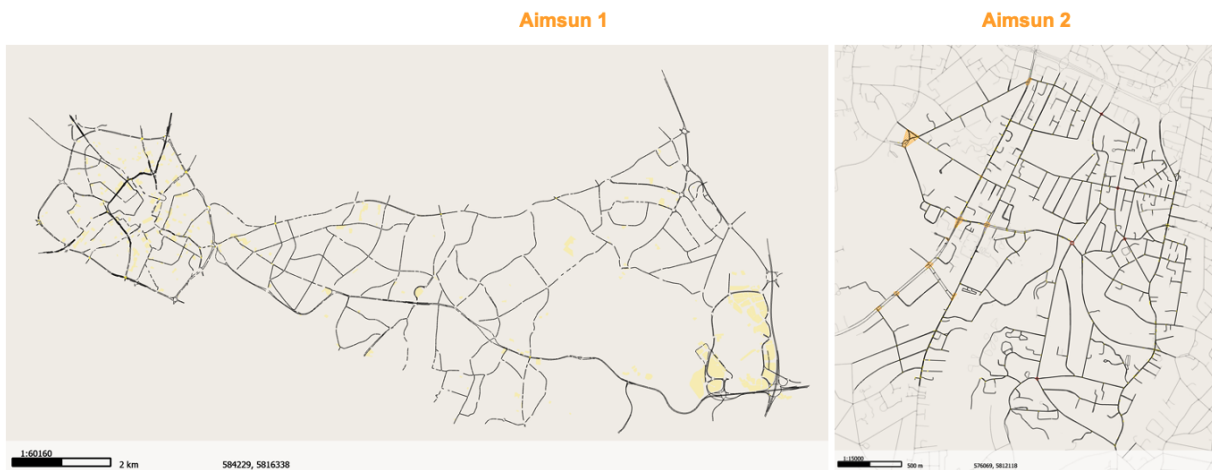


Figure 2-30 Aimsun models for the WM study areas

The microsimulation models for the West Midlands come from another research Project (Lambda-V<sup>10</sup>). Since the models were outdated, there was a need for significant improvements. This included changes to intersection layouts, the introduction of pedestrianized streets, and the addition of new tram lines. Traffic light information was also carefully revised; since traffic control in the study areas had undergone several updates, detailed information provided by Transport for West Midlands (TfWM) ensured the model accurately mirrored current signal operations at key intersections.

The origin-destination (OD) matrices received substantial refinement as well. By incorporating telematics data from the project partner, The Floow, and supplementing it with open data for the region, the matrices became more representative of actual travel patterns. These refinements were further enhanced using proprietary Aimsun tools.

Additionally, the Aimsun 2 model was expanded to include bicycle traffic, and the cycling infrastructure within the area was meticulously improved, ensuring that the representation of all modes of transport was both comprehensive and realistic.

The spatial granularity for ODs is at the LSOA (Lower layer Super Output Areas) level. The key difficulty here was that we have 3 types of trips that are fundamentally different from an analysis perspective, which are:

- Origin and destination within the simulation area. No adjustment needed.

<sup>9</sup> The detail description of these interventions are described in Deliverables 4.1 and 4.2

<sup>10</sup> To know more about the Lambda-V project access: <https://gtr.ukri.org/projects?ref=133558>

- Origin and destination outside the simulation area. In this case, we need to determine the point of entry and exit of the simulation so that it can realistically cross the simulation area.
- Origin and destination are in the simulation area, while the other (destination or origin) is outside the simulation area. In this case, there was a need to determine the entry/exit point of the vehicle.

Aimsun tools have been used to profile the OD matrices in a way that changes over the day, so they are more dynamic, and to scale the demand to fit the traffic flow observed on detectors in the network.

For the Aimsun 2 model (Edgbaston) enhancements, on the right of - 25, an intersection with newly added bicycle lanes and the interactions in the intersection can be seen. For that, traffic light bicycles have been updated as well, since traffic light changes with the introduction of bicycle lanes in the area since the model was first developed.

The calibration process for the Aimsun 2 model (Edgbaston) focused on aligning simulation outcomes with real-world data across various vehicle categories. This calibration was carried out over 12 hours, and the results demonstrated a strong correlation between the model and observed traffic flows, as measured by the GEH statistic <sup>11</sup>—a standard metric in traffic simulation calibration. The high degree of accuracy was anticipated, given that the Edgbaston study area is more compact than Aimsun 1, allowing for greater attention to detail.

Furthermore, because this model includes vulnerable road users (VRUs), calibration efforts took priority, and there was a concerted emphasis on acquiring the most recent traffic signal data from Transport for West Midlands (TfWM). Figure 2-32 shows more details with the car values for the assigned x observed flow.

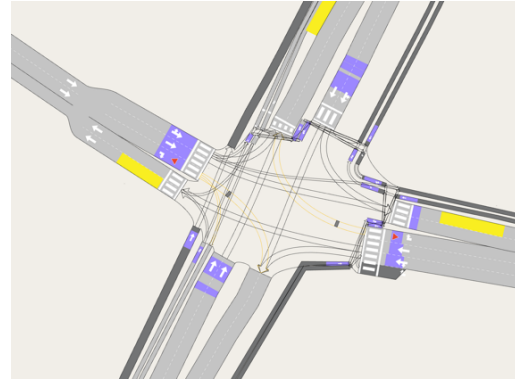


Figure 2-31 Aimsun 2 simulation model enhancements

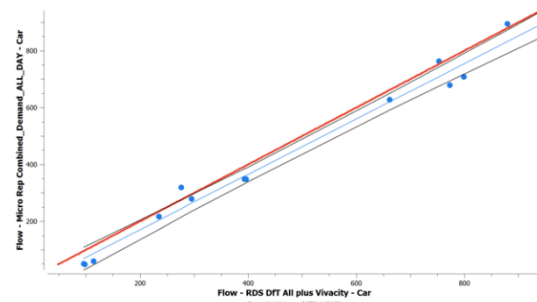


Figure 2-32 Aimsun 2 assigned x observed flow

The calibration process for the Aimsun 1 model, which covers the A45 corridor, involved adjusting the simulation to align with real-world data across various vehicle types. However, the results from this calibration were less accurate compared to those from the Aimsun 2 model. This discrepancy is primarily due to the much larger area covered by the Aimsun 1 model, which made it challenging to achieve the same level of detail and refinement as was possible in the more compact Aimsun 2 area.

Additionally, the calibration of Aimsun 1 faced significant setbacks related to traffic signal information. Due to financial constraints within the city of Birmingham, up-to-date data was only available for a limited number of signalized intersections. Priority was therefore given to updating intersections within the Aimsun 2 model, as it was considered more critical for the study objectives. As a result, the accuracy of the Aimsun 1 model, particularly during the afternoon peak hour, was notably affected, leading to a reduced goodness of fit.

<sup>11</sup> \*The metric used for calibration is the GEH, which is a standard practice in simulation. Further information can be provided within the Aimsun manual *Calibration and Validation - Aimsun Next Users Manual* (Aimsun, 2025).



Ground truth validation data is scarce, i.e., detectors on the road, so the model has been validated against data coming from telematics, which has its sources of error. Hence, the lower-than-usual GEH fit on some detectors cannot be attributed only to poor calibration of the simulation model, but might also be due to some errors present in the validation data.

Still, the result is a GEH of 5.12. Although this value is higher than the desired value of 5, it is just by a very small margin and in any case is well below 10, which is the typical threshold of unacceptability; therefore, it is acceptable.

The chart in Figure 2-33 shows the point cloud of the real data set vs simulation. This is for a series of paths (short trajectories) in the network. Some discrepancy on the lower end is normal and acceptable, as small changes in path preferences can produce this for small demand areas. The key thing is mid-range and large values (centre and top right of the chart). Here we see a quite good alignment in the mid range, and a slight decrease for the large values due to traffic light problems at peak hour on the most heavily demanded sections. Overall, the flow difference from real data to simulation is just over 3% which is very good, given the available data.

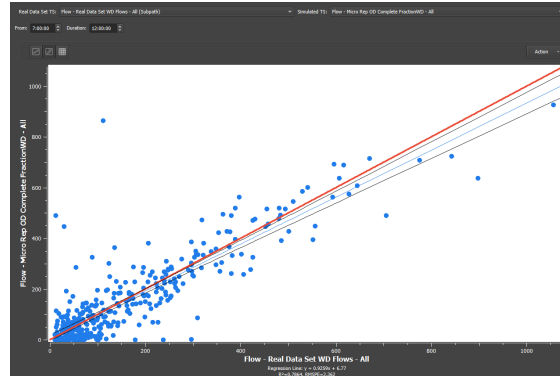


Figure 2-33 Real data x simulation results

In the case of the interventions for WM models, A scenario with speed reduction has been coded into the network, with all urban links with 40 mph speed limits reduced to 30 mph.

A scenario with an AV Operational Design Domain (ODD) was added. This was agreed between the relevant partners. Its key feature was a soft geofencing (virtual boundaries around specific areas and triggering actions when vehicles enter or exit those zones) to control the traffic flow of AV for specific areas or complex turning manoeuvres. It needed to be a soft geofence, as for the sake of result analysis, we need the AVs to reach any part of the network to fulfill trips from any origin to any destination. This is achieved by setting an arbitrarily larger cost for AVs on roads outside the geofenced areas. The larger the cost, the more the AV will try to stay off that part of the network, but if needed, they will still travel into it. AV cost functions for geofencing, share setting up, and visualization

## 3. Integration Protocols

This chapter advances through the framework integration by addressing the technical aspects that need to be in place for the PHOEBE framework to run.

The integration protocols and user guides will be entirely developed by the end of WP5.

The chapter content presents the three key topics for integration:

- Internal data flows and data processing to ensure the transferability of data from one framework stage component to the subsequent stage
- Integration sequence of events represented in the framework, detailed flowchart
- Key Performance Indicators to evaluate interventions

As the simulation is the central hub of processing, this chapter also presents the dedicated instructions for running the four simulations recruited in the framework stages.

### 3.1. Internal Data Flow Matrix processing requirements

The internal data flow matrix structures the representation of how data moves within the PHOEBE Framework. This matrix helps in understanding the flow of information, identifying potential bottlenecks, and ensuring that the necessary processes are in place so that the output of one component can serve as the input for the subsequent component.

In the context of **Deliverable 3.2**, the internal data flow matrix can be used as a map of the data interactions between different components. It ensures that all stakeholders have a clear understanding of how data is being used and transferred, which is crucial for effective collaboration and operationalization of the subsequent calculations.

After designing the internal data flow matrix, it became evident that some outputs could not be directly incorporated as inputs into the subsequent components. This issue arises because specific models require different levels of aggregation. For example, 15-minute vehicle flows generated by the traffic simulation need to be aggregated into hourly values for the risk assessment model. Additionally, the other outputs serve as input variables for modelling. For instance, vehicle trajectories need to be processed to generate conflict surrogate measures.

This means that the operationalisation of the PHOEBE framework demands specific processing scripts to align the internal data specifications. These scripts are essential to ensure that the data is correctly formatted and aggregated to meet the requirements of each model within the framework. The subsequent slide shows the data processing requirements.

Python scripts and APIs were developed to process SQLite and CSV files containing microsimulation results, such as the 85th percentile speed, pedestrian hourly flow, and vehicle trajectories. Additionally, Excel/VBA scripts are employed for specific tasks like processing vehicle hourly flows and generating conflict surrogate measures. The aggregation levels vary depending on the data type and the model requirements, ranging from section IDs to matrix OD levels.

In order to demonstrate the operationalisation of the PHOEBE framework, the project team refers to each use case where this data processing should be performed and identifies the partner responsible for running these scripts. - 1 presents the input data and the processing requirements designed for the PHOEBE application.





*Table 3-1 Internal data matrix*

[illegible]



Table 3-2 Input data specifications and processing requirements

| Inputs                                                                         | Required format | Require processing? | Processing responsible | Script              | Software   | Aggregation level | Connector  | Use case availability | Origin | Destination | Providers       | Recievers      |
|--------------------------------------------------------------------------------|-----------------|---------------------|------------------------|---------------------|------------|-------------------|------------|-----------------------|--------|-------------|-----------------|----------------|
| D3 - All - Microsimulation results - 85th Percentile Speed                     | CSV             | Yes                 | Aimsun                 | Python script / API | Python     | Link/Section      | Section ID | WM Valencia Athens    | TS     | RA          | Floow UPV, NTUA | iRAP           |
| D3 - All - Microsimulation results - Mean Speed                                | CSV             | No                  | -                      | -                   | -          | -                 | -          | WM Valencia Athens    | TS     | RA          | Floow UPV, NTUA | iRAP           |
| D3 - All - Microsimulation results - Speed StDev                               | CSV             | No                  | -                      | -                   | -          | -                 | -          | WM Valencia Athens    | TS     | RA          | Floow UPV, NTUA | iRAP           |
| D3 - All - Microsimulation results - Vehicles hourly flows                     | CSV             | Yes                 | iRAP                   | V3.1 model testbed  | Excel/V BA | Link/section      | Section ID | WM Valencia Athens    | TS     | RA          | Floow UPV, NTUA | iRAP           |
| D80 - Pedestrian trajectories - Ped hourly flow - Along                        | CSV             | Yes                 | AIMSUN                 | Python script / API | Python     | Link/section      | Section ID | Athens                | TS     | RA          | NTUA            | iRAP           |
| D80 - Pedestrian trajectories - Ped hourly flow - Crossing                     | CSV             | Yes                 | Aimsun                 | Python script / API | Python     | Link/section      | Section ID | Athens                | TS     | RA          | NTUA            | iRAP           |
| D3 - All - Microsimulation results - Bic hourly flow - along                   | CSV             | Yes                 | iRAP                   | V3.1 model testbed  | Excel/V BA | Link/section      | Section ID | WM Valencia           | TS     | RA          | Floow UPV       | iRAP           |
| D9 - Estimation of behaviour probabilities - Conflict x crash relationship     | CSV             | Yes                 | Aimsun                 | Python script / API | Python     | Link/section      | Section ID | WM Valencia           | TS     | RA          | Floow UPV       | iRAP           |
| D76 - Segmented OD matrix per mode and gender                                  | CSV             | No                  | -                      | -                   | -          | -                 | OD ID      | WM Valencia Athens    | DM     | TS          | TUM             | Floow UPV NTUA |
| D9 - Estimation of behaviour probabilities - Behavioural parameters            | Text            | No                  | -                      | -                   | -          | -                 | -          | WM Valencia Athens    | BM     | TS          | TUD             | Floow UPV NTUA |
| D9 - Estimation of behaviour probabilities - Individual variable distributions | Text            | No                  | -                      | -                   | -          | -                 | -          | WM Valencia Athens    | BM     | TS          | TUD             | Floow UPV NTUA |
| D8 Star Ratings and FSIs - Star ratings per link                               | CSV             | Yes                 | iRAP                   | V3.1 model testbed  | Excel/V BA | Link/section      | Section ID | WM Valencia Athens    | RA     | TS          | iRAP            | Floow UPV NTUA |
| D8 Star Ratings and FSIs - FSIs per link                                       | CSV             | Yes                 | iRAP                   | V3.1 model testbed  | Excel/V BA | Link/section      | Section ID | WM Valencia Athens    | RA     | TS          | iRAP            | Floow UPV NTUA |
| D10 - Road-related attribute                                                   | CSV             | No                  | -                      | -                   | -          | -                 | Section ID | WM Valencia Athens    | RA     | BM          | iRAP            | TUD            |



| Inputs                                                                     | Required format | Require processing? | Processing responsible | Script                       | Software           | Aggregation level | Connector  | Use case availability | Origin | Destination | Providers       | Recievers |
|----------------------------------------------------------------------------|-----------------|---------------------|------------------------|------------------------------|--------------------|-------------------|------------|-----------------------|--------|-------------|-----------------|-----------|
| D79 - Vehicle trajectories                                                 | TRJ             | Yes                 | TUD                    | Python script                | Python             | Link/section      | Section ID | WM Valencia Athens    | TS     | BM          | Floow UPV, NTUA | TUD       |
| D1 - Conflict analysis (SSAM results) - TTC                                | TRJ             | Yes                 | TUD                    | Python script                | Python             | Link/section      | Section ID | WM Valencia Athens    | TS     | BM          | Floow UPV, NTUA | TUD       |
| D1 - Conflict analysis (SSAM results) - PET                                | TRJ             | Yes                 | TUD                    | Python script                | FHWA SSAM Software | Link/section      | Section ID | WM Valencia Athens    | TS     | BM          | Floow UPV, NTUA | TUD       |
| D77- Skim matrices relative risk (per mode)                                | CSV             | Yes                 | TUM                    | Locally developed code (TUM) | Python             | Matrix - OD level | OD ID      | WM Valencia Athens    | RA     | DM          | iRAP            | TUM       |
| D84 - All - Skim Matrixes (traffic simulation outputs) - Travel Cost       | CSV             | Yes                 | Aimsun                 | Python script / API          |                    | Matrix - OD level | OD ID      | WM Valencia Athens    | TS     | DM          | Floow UPV, NTUA | TUM       |
| D84 - All - Skim Matrixes (traffic simulation outputs) - Travel time - IVT | CSV             | Yes                 | Aimsun                 | Python script / API          |                    | Matrix - OD level | OD ID      | WM Valencia Athens    | TS     | DM          | Floow UPV, NTUA | TUM       |
| D84 - All - Skim Matrixes (traffic simulation outputs) - OD distance       | CSV             | Yes                 | Aimsun                 | Python script / API          |                    | Matrix - OD level | OD ID      | WM Valencia Athens    | TS     | DM          | Floow UPV, NTUA | TUM       |
| D83 - Unsegmented OD matrices                                              | CSV             | No                  | -                      | -                            | -                  | Matrix - OD level | OD ID      | WM Valencia Athens    | TS     | DM          | Floow UPV, NTUA | TUM       |

Where:

BM = Behaviour Models

DM = Demand Models

RS = Risk Assessment Models

TS = traffic simulation

## 3.2. Integration Flow

The PHOEBE framework is divided across three stages:

- Setup stage:** The setup stage provides initial operational results for necessary subsequent analysis. In the baseline, the simulation in the setup stage provides skim matrices relative to travel cost, travel time, travel distance, and number of trips. All are inputs for mode shift. For the after scenario, speed and flow values are also used to generate initial risk values to identify the relative risk between modes. The relative risk is also used in the mode shift distribution. All the components run in parallel for the baseline scenario. In the after scenarios, additional steps are required to ensure the changes are well represented in each component/
- Simulation stage:** At the simulation stage, the mode shift and induced demand in the case of the after scenarios – generate OD matrices segregated by gender and age. These matrices are re-imported into the simulations to run the final results. At this stage, the Behaviour components are plugged into the simulation software to account for how individuals react to baseline or intervention configurations of the network under analysis.

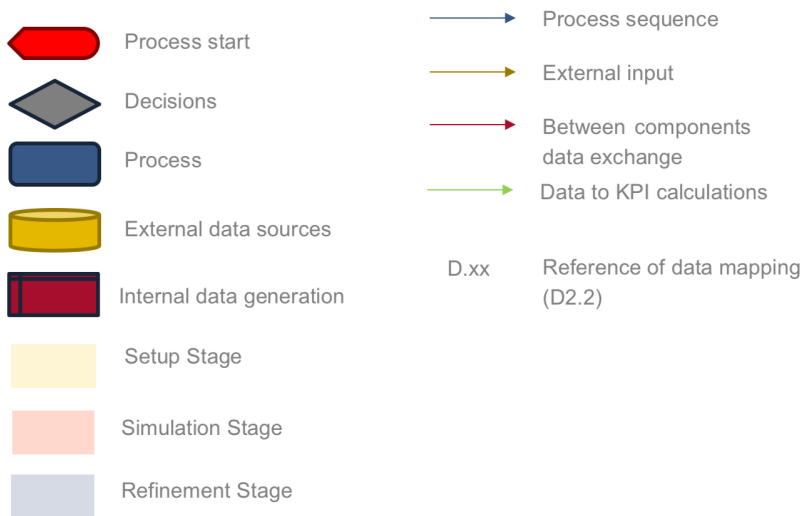


- Refinement stage:** With the final results of the simulation, including mode shift and human behaviour component contributions, the risk models are recalculated to generate the safety KPIs. The FSIs estimations in the refinement stage are also enhanced with the behaviours' contribution.

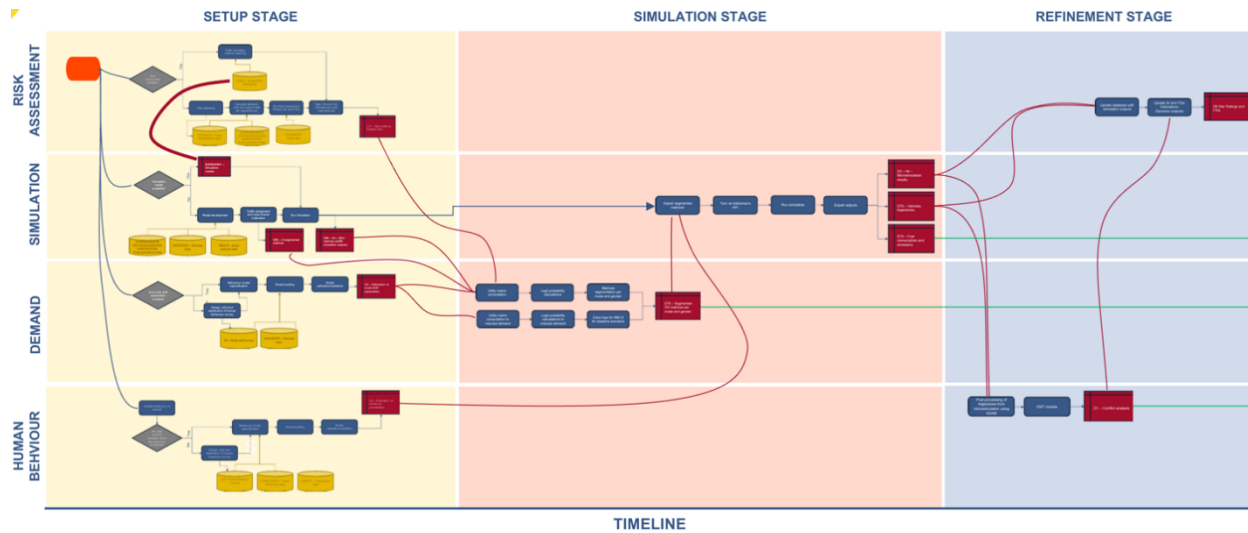
#### How to read the flowchart

To effectively comprehend the PHOEBE framework, it is critical to illustrate each stage within the integration flowchart clearly. The flowchart provides a visual representation that enables users to track the progression of data and processes from the initial setup through simulation and into refinement. Directional arrows are included to clarify the movement of information between stages and components, allowing for a straightforward understanding of how outputs from one phase serve as inputs for the next. The legend present in 1 is essential for better comprehension.

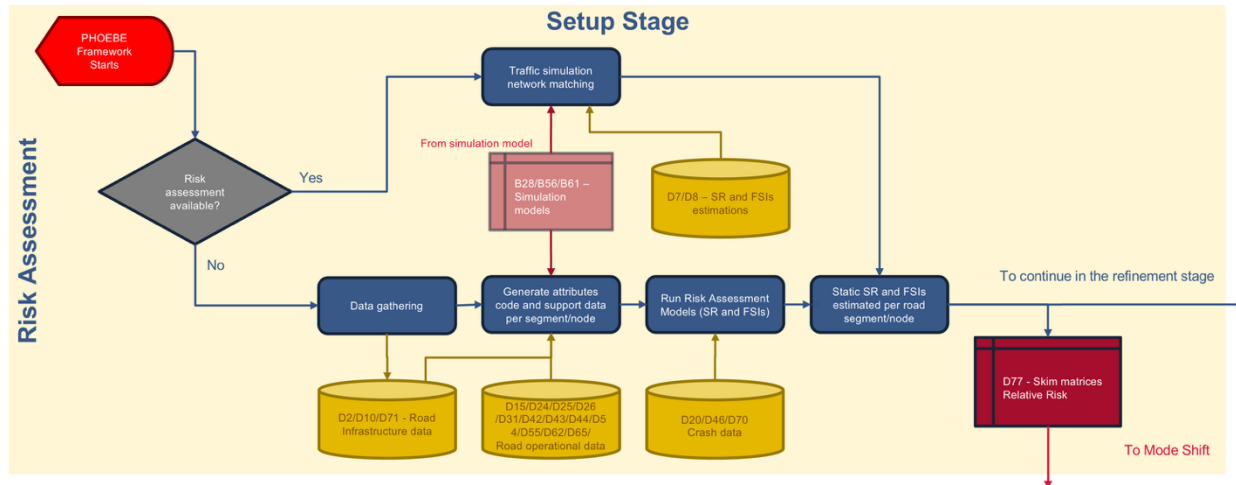
#### Legend



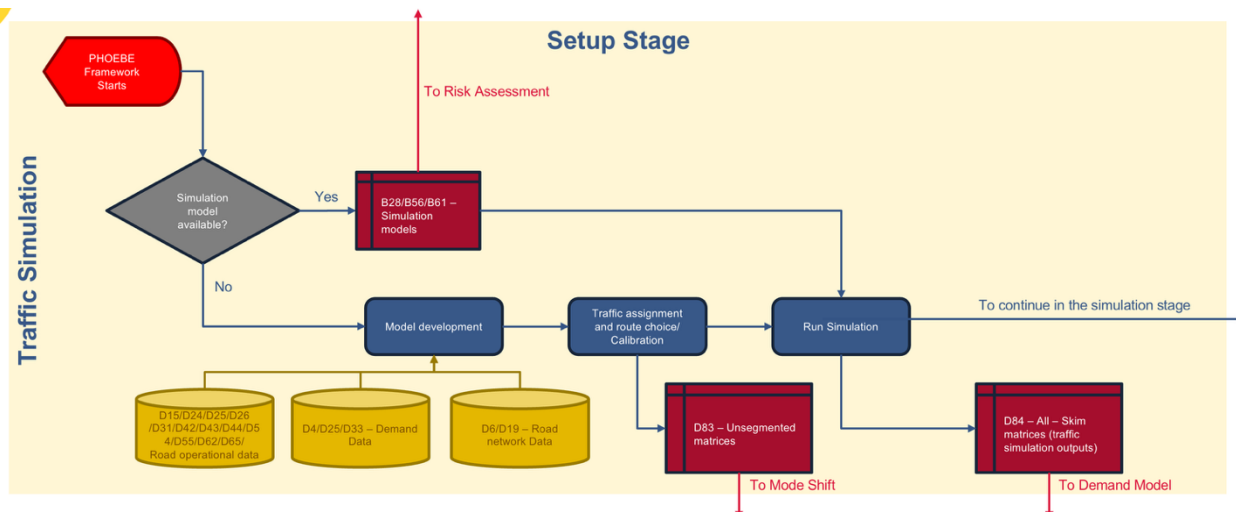
### Flowchart Overview



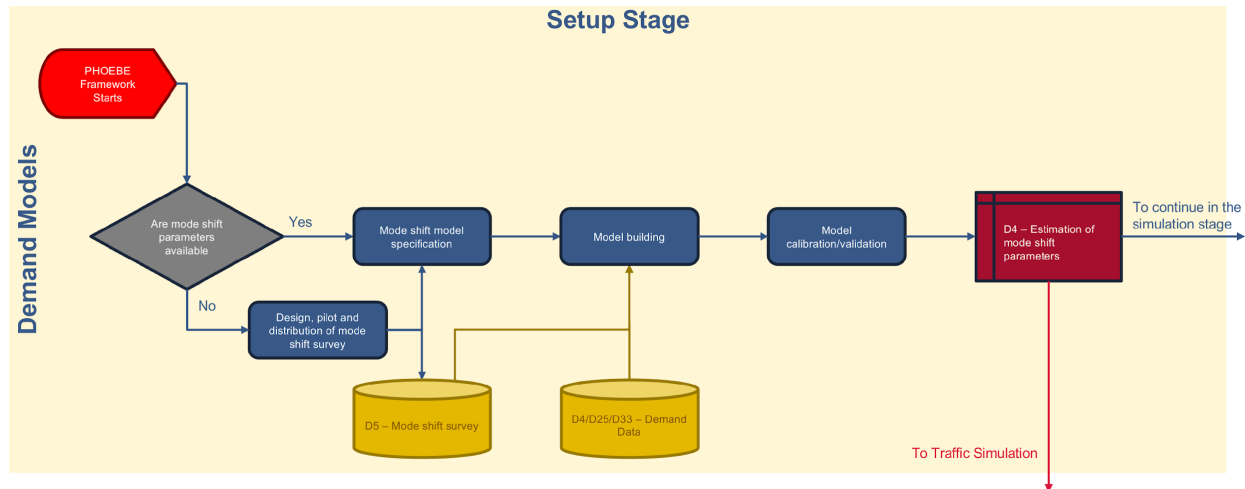
### Setup Stage – Risk Assessment



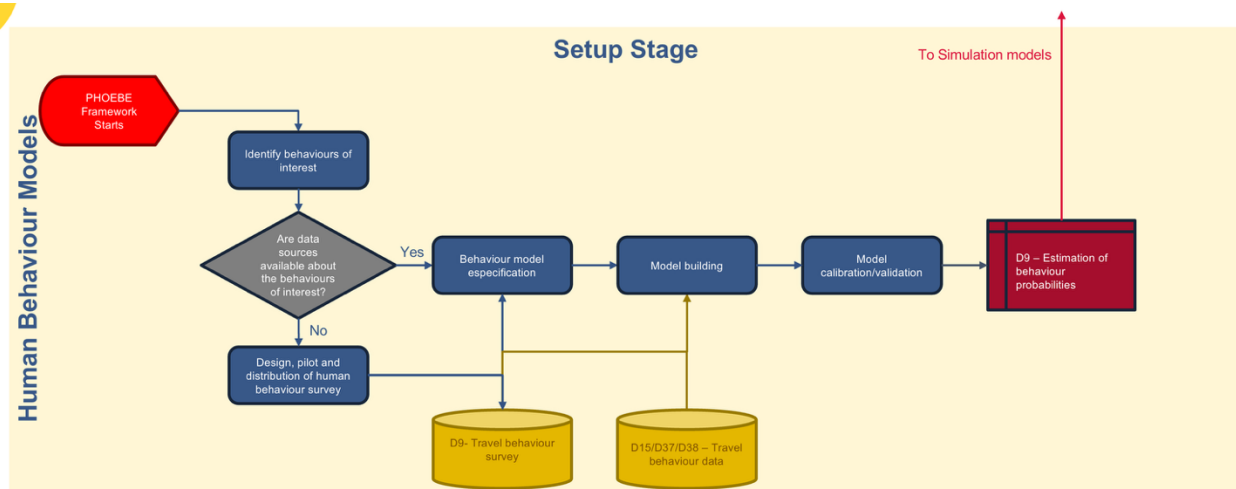
### Setup Stage – Traffic Simulation



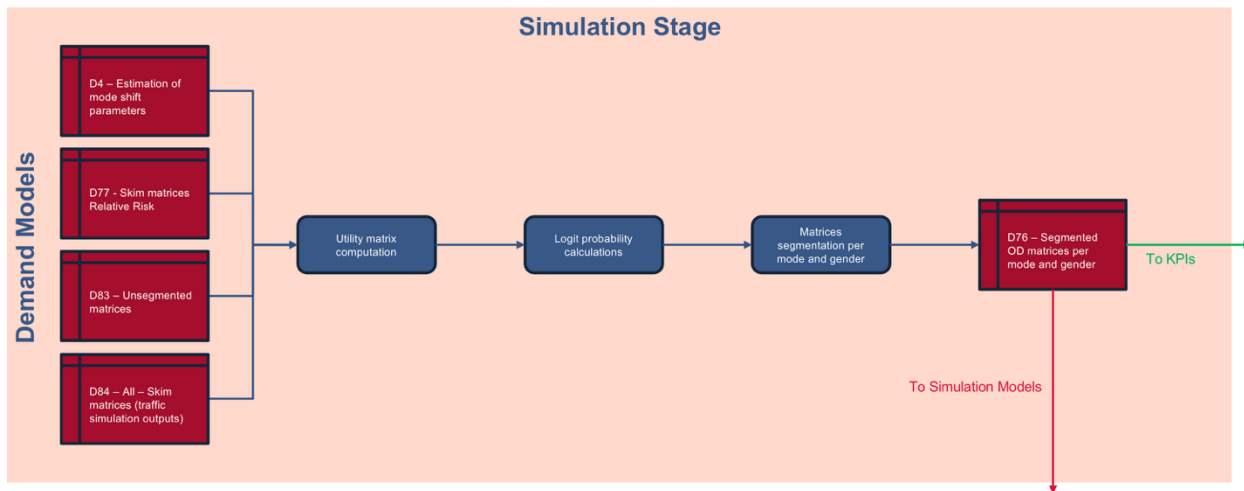
#### Setup Stage – Demand model



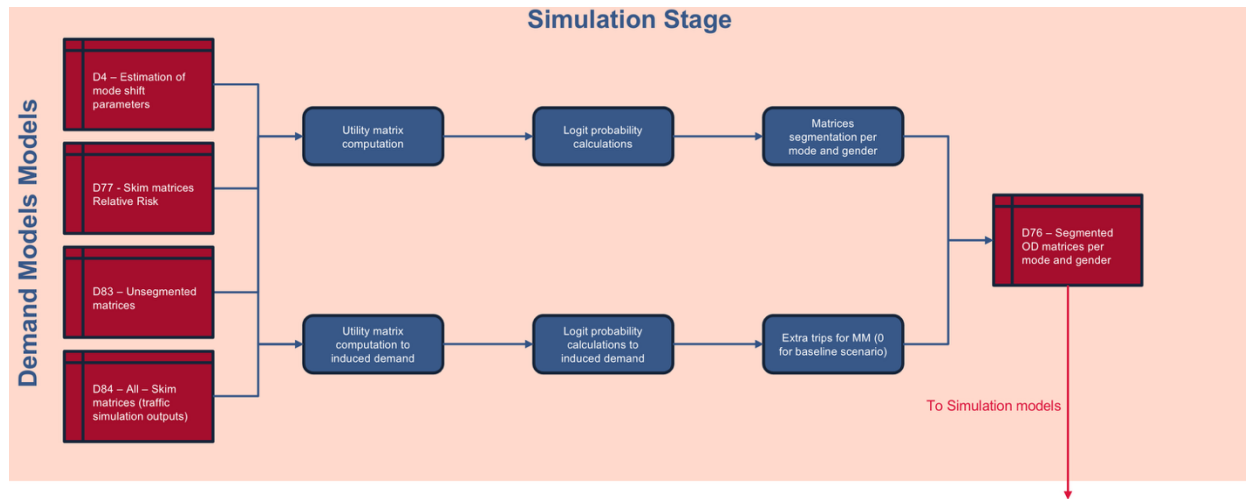
#### Setup Stage – Behavioural models



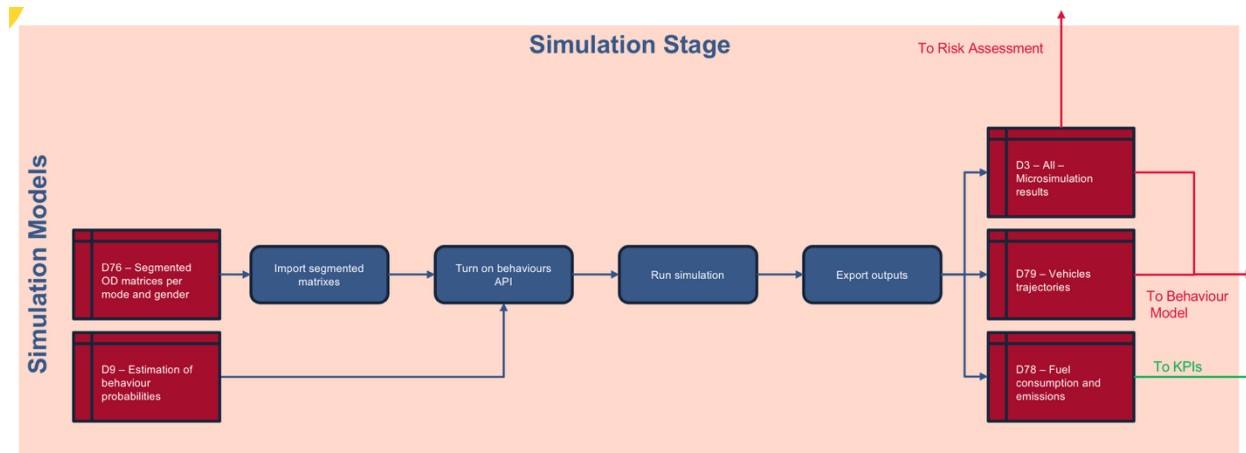
#### Simulation Stage – Demand Models (Baseline)



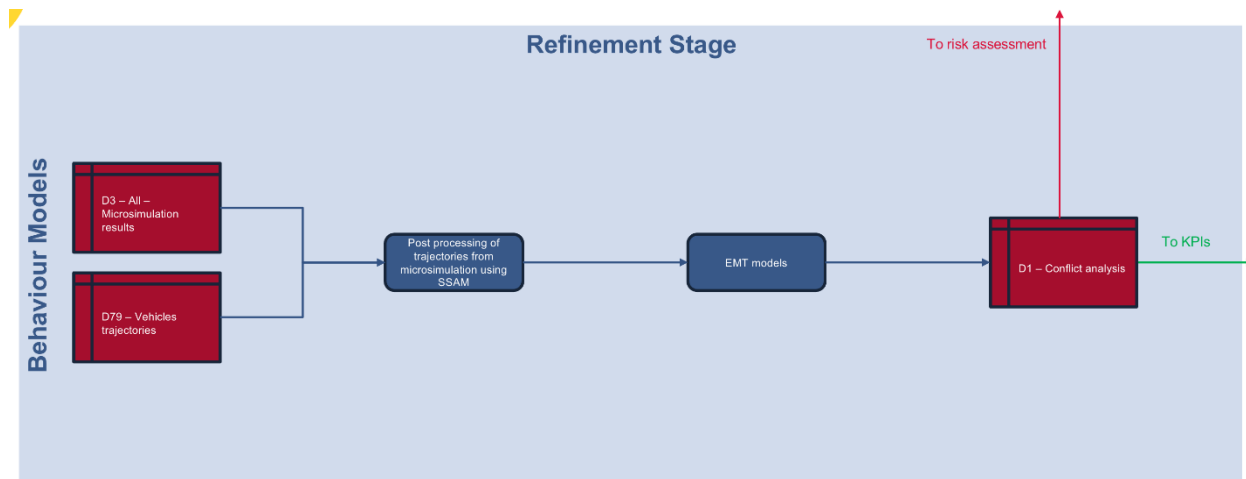
#### Simulation Stage – Demand Models (After)

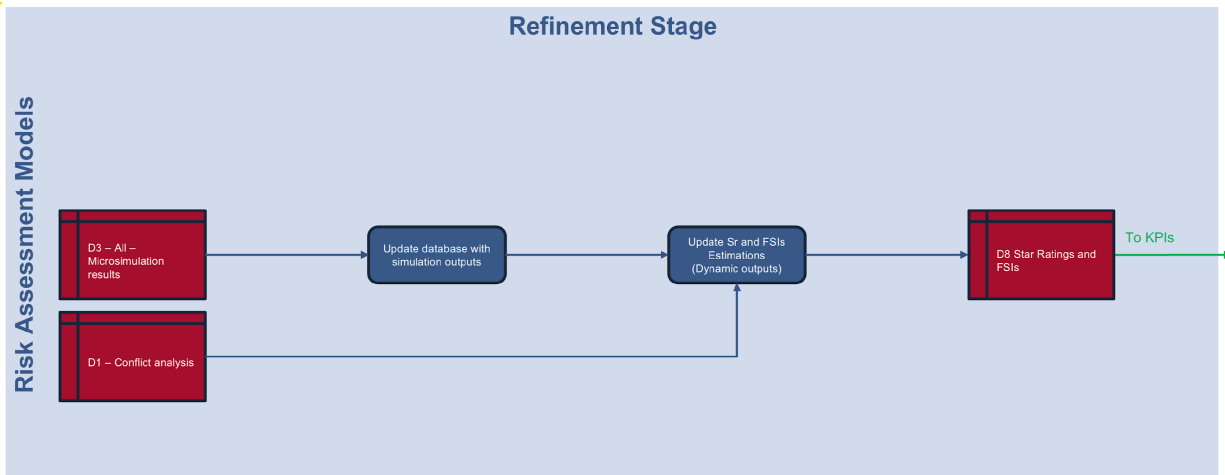


#### Simulation Stage – Traffic Simulation



#### Refinement Stage – Behaviour Models





### 3.3. Simulation Support Materials

In the PHOEBE framework, the simulation software functions as the central integrator, bringing together the various components of the framework into a cohesive whole.

The simulation stages are not only pivotal to the overall integration process but also represent a significant share of the required effort and complexity. Given this central role, careful attention must be paid to the implementation of the simulation stages.

The PHOEBE Framework implementation demands simulations to be run twice in the baseline and twice again in the after scenario.

- **SIM 0.1 – Baseline Setup stage:** This initial simulation stage operates independently, with no dependencies on prior steps. Its primary objective is to generate the required output for the mode shift model: skim matrices.
- **SIM 0.2/3 – Baseline Simulation Stage:** The Baseline Simulation Stage builds upon the initial setup by activating the behavioural component of the PHOEBE framework. This stage depends on several prerequisites, including the availability of segmented matrices, the activation of the Behaviour API, and the configuration of relevant environmental parameters. Once these dependencies are in place, the simulation proceeds to generate two key outputs: structured data stored in SQLite files and SSAM trajectories.
- **SIM 1.1 – After the Setup stage:** The Set-up Stage introduces interventions into the simulation model, marking a shift from baseline conditions to modified scenarios. This stage depends on the successful integration of these interventions within the simulation environment. Its primary output is the generation of updated skim matrices, which reflect the impact of the applied interventions and serve as a foundation for the mode shift and induced demand models.
- **SIM 1.2/3 – After Simulation Stage:** The After Simulation is built on SIM A1, enabling a more nuanced analysis of behavioural responses. This stage relies on several key dependencies: the integration of interventions into the simulation model, the availability of segmented matrices, activation of the Behaviour API, and the configuration of environmental parameters. Upon satisfying these prerequisites, the simulation produces two essential outputs—SQLite files containing structured data and SSAM trajectories that capture detailed behavioural patterns for further evaluation.





A.8 Instructions on how to perform simulations in the AIMSUN Next Software contain the complete list of performance indicators along with the procedures for their calculations.

### 3.4. Performance Indicators

The PHOEBE framework was designed to provide cities with a set of robust performance indicators, empowering them to measure and evaluate the effectiveness of their interventions with precision and objectivity.

A special emphasis is placed on vulnerable road user (VRU) indicators, such as monitoring speed and tracking the modal share of pedestrians and cyclists. The framework's KPIs are crafted to reflect modal split variations across different periods of the day, ensuring a nuanced understanding of mobility patterns and safety outcomes. This comprehensive approach allows urban planners and policymakers to make informed decisions, ultimately fostering safer, more sustainable, and more inclusive urban environments.

The list of performance indicators can be categorized into four groups:

- **Health and Safety: 19 indicators** illustrate how the intervention decreases risk and the incidence of fatal and serious injuries. These indicators also include modifications to infrastructure aimed at enhancing safety for all road users.
- **Mode Shift: 24 indicators** that illustrate how the interventions enhance the frequency of trips using more sustainable modes (non-motorised). These indicators take into account various age groups as well as the differences between men and women.
- **Environment: 2 indicators** based on the simulation calculations of pollutant emissions, calculated based on fleet vehicle types and individual vehicle speed profiles.
- **Operations: 3 indicators** that reflect the operational parameters of the network being studied include network travel time, travel distance, and delay.

#### 3.4.1. Health and Safety Indicators

Table 3-3 outlines the health and safety indicators, their calculation methods, and the trends related to road safety.

Table 3-3 Health and Safety Indicators

| ID   | KPI Name                                                                       | Calculation description                                                                                                              | Desire trend           |
|------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|------------------------|
| HS01 | Total number of fatalities and severe injuries on the network                  | Sum of iRAP fatal and severe injuries estimations per user group in a year                                                           | Smaller the better     |
| HS02 | % of the network above road safety mark (3 stars or better) – Vehicle Occupant | Number of segments in the network with Vehicle Occupant Star Rating greater than three stars divided by the total number of segments | The greater the better |
| HS03 | % of the network above road safety mark (3 stars or better) – Motorcyclist     | Number of segments in the network with Motorcyclist Star Rating greater than three stars divided by the total number of segments     | The greater the better |
| HS04 | % of the network above road safety mark (3 stars or better) – Pedestrian       | Number of segments in the network with Pedestrian Rating greater than three stars divided by the total number of segments            | The greater the better |



| ID   | KPI Name                                                                                                                                                    | Calculation description                                                                                                                                                                                                                                                               | Desire trend           |
|------|-------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|
| HS05 | % of the network above road safety mark (3 stars or better) – Bicyclist                                                                                     | Number of segments in the network with Bicyclist Rating greater than three stars divided by the total number of segments                                                                                                                                                              | The greater the better |
| HS06 | Risk variability within the simulated scenarios                                                                                                             | Standard deviation of Star Rating Scores within the simulated hourly periods                                                                                                                                                                                                          | Smaller the better     |
| HS07 | Average road safety risk on nodes - Vehicle Occupant                                                                                                        | Average Vehicle Occupant Star Rating Score where the intersection is coded as present (<> None)                                                                                                                                                                                       | Smaller the better     |
| HS08 | Average road safety risk on nodes - Motorcyclist                                                                                                            | Average Motorcyclist Star Rating Score where the intersection is coded as present (<> None)                                                                                                                                                                                           | Smaller the better     |
| HS09 | Average road safety risk on nodes - Pedestrian                                                                                                              | Average Pedestrian Star Rating Score where the intersection is coded as present (<> None)                                                                                                                                                                                             | Smaller the better     |
| HS10 | Average road safety risk on nodes - Bicyclists                                                                                                              | Average Bicyclist Star Rating Score where the intersection is coded as present (<> None)                                                                                                                                                                                              | Smaller the better     |
| HS11 | Average road safety risk on links/sections - Vehicle Occupant                                                                                               | Average Vehicle Occupant Star Rating Score where the intersection is coded as not present (= None)                                                                                                                                                                                    | Smaller the better     |
| HS12 | Average road safety risk on links/sections - Motorcyclist                                                                                                   | Average Motorcyclist Star Rating Score, where the intersection is coded as not present (= None)                                                                                                                                                                                       | Smaller the better     |
| HS13 | Average road safety risk on links/sections - Pedestrian                                                                                                     | Average Pedestrian Star Rating Score where the intersection is coded as not present (= None)                                                                                                                                                                                          | Smaller the better     |
| HS14 | Average road safety risk on links/sections - Bicyclists                                                                                                     | Average Bicyclist Star Rating Score, where the intersection is coded as not present (= None)                                                                                                                                                                                          | Smaller the better     |
| HS15 | % of the road network where the operating speed (85th) is above the speed limit                                                                             | Number of segments where <i>Operating Speed (85<sup>th</sup> percentile)</i> > <i>Speed limit</i> divided by the total number of segments                                                                                                                                             | Smaller the better     |
| HS16 | % of road network with good quality sidewalk where operating speed (85 <sup>th</sup> ) is over 30km/h or 20 mph, and a pedestrian is walking along the flow | Number of segments where Operating Speed (85 <sup>th</sup> percentile) > 30 km/h or 20mph, pedestrians along flows > 0, and good quality sidewalk coded (codes 1, 2,3, OR 4) divided by the number of segments where Operating Speed (85 <sup>th</sup> percentile) > 30 km/h or 20mph | The greater the better |
| HS17 | % of road network with crossing facility where operating speed (85th) is over 30km/h or 20 mph, and there is a pedestrian crossing flow                     | Number of segments where Operating Speed (85 <sup>th</sup> percentile) > 30 km/h or 20mph, pedestrians crossing flows > 0, and pedestrian crossing is presented (<> No facility) divided by                                                                                           | The greater the better |



| ID   | KPI Name                                                                                                        | Calculation description                                                                                                                                                                                                                                | Desire trend           |
|------|-----------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|
|      |                                                                                                                 | the number of segments where Operating Speed (85 <sup>th</sup> percentile)> 30 km/h or 20mph                                                                                                                                                           |                        |
| HS18 | % of pedestrian crossings that are adequately signed and well-maintained                                        | Number of segments where pedestrian crossing is presented (<> No facility) and crossing quality is good, divided by the number of segments where pedestrian crossing is presented                                                                      | The greater the better |
| HS19 | % of road network with bicycle facility where operating speed (85th) is over 30km/h and there is bicyclist flow | Number of segments where Operating Speed (85th percentile)> 30 km/h or 20mph, bicyclists flows > 0, and Facility for bicycle is presented (<> No facility) divided by the number of segments where Operating Speed (85th percentile)> 30 km/h or 20mph | The greater the better |

### 3.4.2. Demand indicators

Table 3-4 outlines the demand indicators, their calculation methods, and the trends related to road safety.

Table 3-4 Demand Indicators

| ID   | KPI Name                                                       | Calculation description                                                                                    | Desire trend           |
|------|----------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|------------------------|
| MS01 | Participation in non-motorised trips - Women - Age group 18-24 | Total number of trips made by Women (18-24) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS02 | Participation in non-motorised trips - Women - Age group 25-34 | Total number of trips made by Women (25-34) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS03 | Participation in non-motorised trips - Women - Age group 35-44 | Total number of trips made by Women (35-44) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS04 | Participation in non-motorised trips - Women - Age group 45-54 | Total number of trips made by Women (45-54) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS05 | Participation in non-motorised trips - Women - Age group 55-69 | Total number of trips made by Women (55-69) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS06 | Participation in non-motorised trips - Women - Age group 70+   | Total number of trips made by Women (70+) with private micromobility, shared micromobility, and walking.   | The greater the better |
| MS07 | Participation in motorised trips - Women - Age group 18-24     | Total number of trips made by Women (18-24) with car, public transport, and motorcycle.                    | Smaller the better     |



| ID   | KPI Name                                                     | Calculation description                                                                                  | Desire trend           |
|------|--------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|------------------------|
| MS08 | Participation in motorised trips - Women - Age group 25-34   | Total number of trips made by Women (25-34) with car, public transport, and motorcycle.                  | Smaller the better     |
| MS09 | Participation in motorised trips - Women - Age group 35-44   | Total number of trips made by Women (35-44) with car, public transport, and motorcycle.                  | Smaller the better     |
| MS10 | Participation in motorised trips - Women - Age group 45-54   | Total number of trips made by Women (45-54) with car, public transport, and motorcycle.                  | Smaller the better     |
| MS11 | Participation in motorised trips - Women - Age group 55-69   | Total number of trips made by Women (55-69) with car, public transport, and motorcycle.                  | Smaller the better     |
| MS12 | Participation in motorised trips - Women - Age group 70+     | Total number of trips made by Women (70+) with car, public transport, and motorcycle.                    | Smaller the better     |
| MS13 | Participation in non-motorised trips - Men - Age group 18-24 | Total number of trips made by Men (18-24) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS14 | Participation in non-motorised trips - Men - Age group 25-34 | Total number of trips made by Men (25-34) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS15 | Participation in non-motorised trips - Men - Age group 35-44 | Total number of trips made by Men (35-44) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS16 | Participation in non-motorised trips - Men - Age group 45-54 | Total number of trips made by Men (45-54) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS17 | Participation in non-motorised trips - Men - Age group 55-69 | Total number of trips made by Men (55-69) with private micromobility, shared micromobility, and walking. | The greater the better |
| MS18 | Participation in non-motorised trips - Men - Age group 70+   | Total number of trips made by Men (70+) with private micromobility, shared micromobility, and walking.   | The greater the better |
| MS19 | Participation in motorised trips - Men - Age group 18-24     | Total number of trips made by Men (18-24) with a car, public transport, and motorcycle.                  | Smaller the better     |
| MS20 | Participation in motorised trips - Men - Age group 25-34     | Total number of trips made by Men (25-34) with car, public transport, and motorcycle.                    | Smaller the better     |
| MS21 | Participation in motorised trips - Men - Age group 35-44     | Total number of trips made by Men (35-44) with car, public transport, and motorcycle.                    | Smaller the better     |
| MS22 | Participation in motorised trips - Men - Age group 45-54     | Total number of trips made by Men (45-54) with a car, public transport, and motorcycle.                  | Smaller the better     |



| ID   | KPI Name                                                 | Calculation description                                                               | Desire trend       |
|------|----------------------------------------------------------|---------------------------------------------------------------------------------------|--------------------|
| MS23 | Participation in motorised trips - Men - Age group 55-69 | Total number of trips made by Men (55-69) with car, public transport, and motorcycle. | Smaller the better |
| MS24 | Participation in motorised trips - Men - Age group 70+   | Total number of trips made by Men (70+) with a car, public transport, and motorcycle. | Smaller the better |

#### 3.4.3. Operational indicators

Table 3-5 outlines the operational indicators, their calculation methods, and the trends related to road safety.

Table 3-5 Operational Indicators

| ID  | KPI Name                | Calculation description                                                                                                                                                                                              | Desire trend                                                                                                                                                                                                         |
|-----|-------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| OP1 | Network travel time     | Addition of the time spent in the network of all vehicles and pedestrians, more info in the Aimsun manual: Calculate Traffic Statistics - Aimsun Next Users Manual (Aimsun, 2025).                                   | Smaller the better                                                                                                                                                                                                   |
| OP2 | Network travel distance | Addition of the distance travelled through the network of all vehicles and pedestrians. More information can be found in the Aimsun manual: Calculate Traffic Statistics - Aimsun Next Users Manual (Aimsun, 2025).. | Smaller the better                                                                                                                                                                                                   |
| OP3 | Network delay           | Average delay incurred by all vehicles in the network in seconds per km travelled and by vehicle.                                                                                                                    | Smaller the better*<br>Since it does not weigh the vehicle delay per the vehicle occupants, in some instances, a larger total delay might represent a better situation, i.e, a more minor total delay per passenger. |

#### 3.4.4. Environmental indicators

Table 3-6 outlines the environmental indicators, their calculation methods, and the trends related to road safety.



Table 3-6 Environmental Indicators

| ID   | KPI Name                  | Calculation description                                                                                                                                                                             | Desire trend       |
|------|---------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------|
| EN01 | Pollutant Emissions – CO2 | Based on fleet vehicle types and individual vehicle speed profiles as described in the Aimsun manual, the model used is the London Emission Model, Environmental Models - Aimsun Next Users Manual. | Smaller the better |
| EN02 | Pollutant Emissions – NO2 | Based on fleet vehicle types and individual vehicle speed profiles as described in the Aimsun manual, the model used is the London Emission Model, Environmental Models - Aimsun Next Users Manual. | Smaller the better |



## 4. Integration Trial Results

Each city tested various interventions—such as speed limit reductions, micromobility enhancements, and infrastructure changes — using traffic microsimulation and behavioural modelling. The chapter presents the results for each step of the framework. Subsequently, the performance indicators relevant for each intervention and additional analysis on the benefits of integration are shown as well.

### 4.1. Assumptions and Limitations

#### Extrapolation to determine the total demand:

Designing a realistic mode-choice model begins with a handful of disciplined assumptions that turn sketchy data into a coherent picture. First, overall trip volume in each study area is inferred by *extrapolating from car counts*. In general, the car travel demand is the best-measured/counted demand in any city's context. Thus, extrapolating the total travel demand using car demand and the real-world modal share of the use cases is the best possible solution in the absence of such data.

#### Sociodemographic segmentation:

Next comes *sociodemographic segmentation*. Raw demand is sliced by age and gender to acknowledge that different cohorts value time, cost, and comfort differently. Age is introduced through a simple device: the midpoint of a respondent's age band (AGEMP). Someone in the 18–24 bracket is represented by a single, intuitively meaningful number 21. Gender enters as a binary dummy with males as the reference group, allowing the model to pick up systematic deviations among women without bloating the variable list.

#### Calibration:

The third step, *calibration*, tunes the model so its base-case predictions mirror today's observed reality. Alternative-Specific Constants—essentially built-in preferences for each transport mode—are iteratively adjusted until the simulated modal split lines up with measured shares. Only once this harmony is reached can the model credibly test policy scenarios.

#### Other assumptions for model applications:

Specific values (e.g., AWET), required as inputs for the mode choice model during application, were assumed based on consultation with use case leaders and a review of relevant literature. These assumptions were necessary, as the values were not directly obtainable from the simulation system. The subsequent slides list these assumptions. It should be noted that some of the listed values are not the variables of interest themselves but are instead used to derive those variables. For example, since walking is not explicitly represented in the simulation system, walking travel time is estimated using average walking speed and the shortest travel distance.

#### Usage of the shortest Origin-Destination (OD) distance:

In order to calculate the mode choice and induced demand:

- Travel distance of Origin-Destination (OD) is a standard impedance that affects the mode choice.
- The mode choice and induced demand models thus use the travel distance (OD) to compute the modal shares.
- In a big network/graph (even if edges sparsely connect it), there can be a large number of valid paths joining a pair of origin and destination.





- The shortest distances between the zones are used as the closest proxy for the calculations.
- The shortest distance matrix is procured from the traffic microsimulation model.
- There can be multiple distances between A and C, e.g., 7 (ABC), 9 (AEC), 5 (AC), 18.5 (AEFDEC), etc.
- However, there is only one shortest distance in this case, i.e., 5 (AC).
- The mode choice and induced demand models assume this distance as the impedance between the origin and destination.

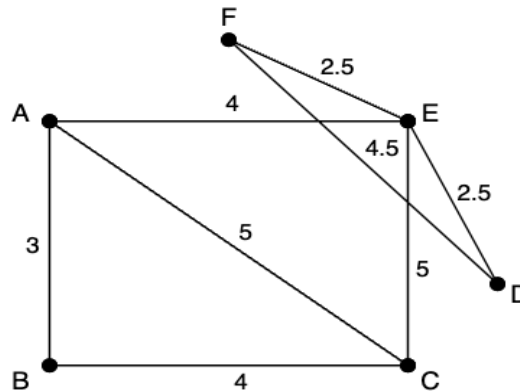


Figure 4-1 Shortest Origin-Destination distance results

#### Induced demand:

In addition to the Mode choice model, the Induced demand models have certain inherent assumptions and limitations. The basic assumptions encompassing predictors remain like those of the mode choice models.

In addition to the above:

- The Induced demand model is not calibrated because of the absence of corresponding real-world data.
- The induced demand model is developed only for shared micromobility, and the induced trips are only calculated for the micromobility users. The demand estimated for the shared micromobility based on the mode choice model is utilised to determine the existing micromobility users. The existing micromobility users are derived from the response to the question asking respondents whether they are existing micromobility users or not.

## 4.2. Use Case Integration Results

The following section presents the indicators obtained as a result of the application of the framework. As presented in section 3.1.1, all the framework stages need to be completed to generate the indicators.

### 4.2.1. Athens

The demonstration of the application of the PHOEBE Framework in deliverable D3.2 will be based on two interventions:

### 3.2 – Finalized models/simulation environments, methodology factsheets and users support materials

- Intervention 1: The scenario represents the interventions for the Athens Great Walk project. More about this specific intervention project was presented in Deliverable 4.1
- Intervention 2: The scenario represents the interventions for the Athens Great Walk project, plus the reduction of the speed limit in the entire study area to 30km/h.

The simulation model covered an area of central Athens of approximately 3 km<sup>2</sup> and included 188 nodes and 428 road segments, with a total road length of 47 km.

The model included five types of users: private cars, trucks, buses, taxis, and pedestrians.

The simulation was conducted during the morning peak hour between 08:00 and 09:00 a.m.

Simulation outputs were recorded across 15-minute time intervals throughout the one-hour simulation period.

A total of three scenarios were modeled:

- **Scenario 0 (baseline):** representing conditions before any intervention implementation.
- **Scenario 1:** representing conditions after intervention one is implemented
- **Scenario 2:** representing conditions after interventions 1 and 2 are implemented

For each scenario, 10 different replications with random seeds were simulated.

Table 4-1 presents the results of the application of the PHOEBE framework in the form of the indicators.

**Preliminary results. Results will be refined and validates in posterior tasks.**

Table 4-1 Indicator results for Athens

| ID   | KPI Name                                                                       | Baseline<br>1 | Scenario<br>1 | Scenario<br>2 |
|------|--------------------------------------------------------------------------------|---------------|---------------|---------------|
| HS01 | Total number of fatalities and severe injuries on the network                  | 66            | 58            | 39            |
| HS02 | % of the network above road safety mark (3 stars or better) – Vehicle Occupant | 99%           | 99%           | 100%          |
| HS03 | % of the network above road safety mark (3 stars or better) – Motorcyclist     | 97%           | 98%           | 99%           |
| HS04 | % of the network above road safety mark (3 stars or better) – Pedestrian       | 85%           | 86%           | 94%           |
| HS05 | % of the network above road safety mark (3 stars or better) – Bicyclist        | 76%           | 77%           | 90%           |
| HS07 | Average road safety risk on nodes - Vehicle Occupant                           | 0.121         | 0.064         | 0.039         |
| HS08 | Average road safety risk on nodes - Motorcyclist                               | 0.121         | 0.11          | 0.08          |



| ID   | KPI Name                                                                                                                                       | Baseline<br>1 | Scenario<br>1 | Scenario<br>2 |
|------|------------------------------------------------------------------------------------------------------------------------------------------------|---------------|---------------|---------------|
| HS09 | Average road safety risk on nodes - Pedestrian                                                                                                 | 0.169         | 0.183         | 0.111         |
| HS10 | Average road safety risk on nodes - Bicyclist                                                                                                  | 0.008         | 0.008         | 0.005         |
| HS11 | Average road safety risk on links/sections - Vehicle Occupant                                                                                  | 2.009         | 2.029         | 0.933         |
| HS12 | Average road safety risk on links/sections - Motorcyclist                                                                                      | 2.034         | 2.027         | 0.905         |
| HS13 | Average road safety risk on links/sections - Pedestrian                                                                                        | 18.795        | 19.05         | 5.901         |
| HS14 | Average road safety risk on links/sections - Bicyclists                                                                                        | 24.68         | 25.489        | 9.779         |
| HS15 | % of the road network where the operating speed (85th) is above the speed limit                                                                | 25.50%        | 11.20%        | 37.70%        |
| HS16 | % of road network with good quality sidewalk where operating speed (85th) is over 30km/h or 20 mph, and a pedestrian is walking along the flow | 0.00%         | 0.00%         | 1.00%         |
| HS17 | % of road network with crossing facility where operating speed (85th) is over 30km/h or 20 mph, and there is a pedestrian crossing flow        | 0.00%         | 0.00%         | 0.00%         |
| HS18 | % of pedestrian crossings that are adequately signed and well-maintained                                                                       | 0.00%         | 0.00%         | 0.00%         |
| HS19 | % of road network with bicycle facility where operating speed (85th) is over 30km/h and there is bicyclist flow                                | 0.00%         | 0.00%         | 0.00%         |
| OP01 | Network travel time (h)                                                                                                                        | 214.27        | 140.36        | 209.68        |
| OP02 | Network travel distance (km)                                                                                                                   | 23313.85      | 20320.50      | 19727.41      |
| OP03 | Network delay (s)                                                                                                                              | 115.78        | 106.07        | 118.69        |
| EN01 | Pollutant Emissions – CO <sub>2</sub> (g)                                                                                                      | 5878436.61    | 5022144.31    | 5662815.65    |



| ID   | KPI Name                      | Baseline   | Scenario   | Scenario   |
|------|-------------------------------|------------|------------|------------|
|      |                               | 1          | 1          | 2          |
| EN02 | Pollutant Emissions – NOx (g) | 8565.59613 | 7994.80663 | 9161.73247 |

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#### 4.2.1.1. Additional analyses - Baseline results for before/after speeding behaviour model integration

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#### 4.2.2. Valencia

The demonstration of the application of the PHOEBE Framework in deliverable D3.2 will be based on four interventions:

- Intervention 1 extends the off-road bike path solution along Avenida Hermanos Machado by altering the priority of the bus lane to facilitate the construction of the off-road cycle path.
- Intervention 2: Intervention 2 tests the establishment of variable speed limits in different road lanes.
- Intervention 3: Intervention 3 explores an increase in the micro mobility share.
- Intervention 4: Intervention 4 tests the city's new parking solution of adding a parking lane next to the median.

The simulation model reached approximately **5 km<sup>2</sup>** and included 289 nodes and 1765 road segments, with a total road length of 125 km.

The model included **three types of users**: private cars, micromobility (bicycles and e-scooters), and buses. The latter were represented as public transport lines rather than through OD matrices.

The simulation was conducted over **four time periods**:

- AM: 5:00 AM to 10:00 AM
- IP (interpeak): 10:00 AM to 2:00 PM
- PM: 3:00 PM to 7:00 PM
- NOCHE (night): 8:00 PM to 12:00 AM

Simulation outputs were recorded across **15-minute time intervals**.

A total of five scenarios were modeled:

- **Scenario 0 (baseline)**: It represents conditions before any intervention implementation.
- **Scenario 1**: Bike lane lowered to road level from Juan XXIII St. to Conde Lumiares St.



- **Scenario 2:** The speed limit is reduced to 30 kph in the closest lane to the adjacent bike lane.
- **Scenario 3:** Micromobility usage is increased by 30%.
- **Scenario 4:** Additional parking lots at Naranjos Av., reducing the number of lanes for motor vehicles.

Table 4-2 presents the results of the application of the PHOEBE framework in the form of the indicators. As explained in section 3.2, all the framework stages need to be completed to generate the indicators.

**Preliminary results. Results will be refined and validates in posterior tasks.**

Table 4-2 Indicator results for Valencia

| ID   | KPI Name                                                                       | Baseline<br>1 | Scenario<br>1 | Scenario<br>2 | Scenario<br>3 | Scenario<br>4 |
|------|--------------------------------------------------------------------------------|---------------|---------------|---------------|---------------|---------------|
| HS01 | Total number of fatalities and severe injuries on the network                  | 9             | 9             | 8             | 10            | 8             |
| HS02 | % of the network above road safety mark (3 stars or better) – Vehicle Occupant | 93.70%        | 95.33%        | 97.02%        | 94.72%        | 94.73%        |
| HS03 | % of the network above road safety mark (3 stars or better) – Motorcyclist     | 88.03%        | 90.13%        | 91.45%        | 88.88%        | 88.88%        |
| HS04 | % of the network above road safety mark (3 stars or better) – Pedestrian       | 61.71%        | 49.85%        | 50.65%        | 49.74%        | 53.77%        |
| HS05 | % of the network above road safety mark (3 stars or better) – Bicyclist        | 79.57%        | 79.62%        | 80.08%        | 80.64%        | 79.23%        |
| HS07 | Average road safety risk on nodes - Vehicle Occupant                           | 7.73          | 11.65         | 0.29          | 6.67          | 6.48          |
| HS08 | Average road safety risk on nodes - Motorcyclist                               | 10.68         | 16.08         | 0.46          | 9.98          | 9.66          |
| HS09 | Average road safety risk on nodes - Pedestrian                                 | 0.27          | 0.78          | 0.37          | 0.36          | 8.04          |
| HS10 | Average road safety risk on nodes - Bicyclists                                 | 0.02          | 0.04          | 0.02          | 0.02          | 0.02          |
| HS11 | Average road safety risk on links/sections - Vehicle Occupant                  | 3.14          | 5.81          | 2.78          | 2.82          | 2.77          |
| HS12 | Average road safety risk on links/sections - Motorcyclist                      | 4.06          | 7.53          | 3.61          | 3.66          | 3.60          |



| ID   | KPI Name                                                                                                                                       | Baseline<br>1 | Scenario<br>1 | Scenario<br>2 | Scenario<br>3 | Scenario<br>4 |
|------|------------------------------------------------------------------------------------------------------------------------------------------------|---------------|---------------|---------------|---------------|---------------|
| HS13 | Average road safety risk on links/sections - Pedestrian                                                                                        | 24.51         | 59.85         | 30.73         | 30.74         | 38.11         |
| HS14 | Average road safety risk on links/sections - Bicyclists                                                                                        | 17.81         | 33.60         | 16.88         | 16.89         | 16.69         |
| HS15 | % of the road network where the operating speed (85th) is above the speed limit                                                                | 4.89%         | 3.52%         | 7.46%         | 7.46%         | 7.42%         |
| HS16 | % of road network with good quality sidewalk where operating speed (85th) is over 30km/h or 20 mph, and a pedestrian is walking along the flow | 0.00%         | 0.00%         | 0.00%         | 0.00%         | 0.00%         |
| HS17 | % of road network with crossing facility where operating speed (85th) is over 30km/h or 20 mph, and there is a pedestrian crossing flow        | 12.15%        | 12.58%        | 12.68%        | 13.03%        | 57.73%        |
| HS18 | % of pedestrian crossings that are adequately signed and well-maintained                                                                       | 1.96%         | 2.84%         | 0.95%         | 0.95%         | 0.94%         |
| HS19 | % of road network with bicycle facility where operating speed (85th) is over 30km/h and there is bicyclist flow                                | 0.93%         | 1.00%         | 1.00%         | 1.03%         | 9.62%         |
| OP01 | Network travel time (h)                                                                                                                        | 120.91        | 189.76        | 104.98        | 110.34        | 270.46        |
| OP02 | Network travel distance (km)                                                                                                                   | 129594.86     | 129879.84     | 130470.99     | 130513.18     | 130188.44     |
| OP03 | Network delay (s)                                                                                                                              | 78.10         | 84.11         | 78.41         | 79.67         | 88.11         |
| EN01 | Pollutant Emissions – CO <sub>2</sub> (g)                                                                                                      | 18521078.5    | 18714633.87   | 18626666      | 18479078.7    | 19225488      |
| EN02 | Pollutant Emissions – NO <sub>x</sub> (g)                                                                                                      | 17474.7868    | 17649.78      | 17577.8588    | 17435.646     | 18087.9074    |

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### 4.2.2.1. Dynamic Risks Charts

#### Intervention 1 - Dynamic Risk – Cyclists - Avenida del German Machado

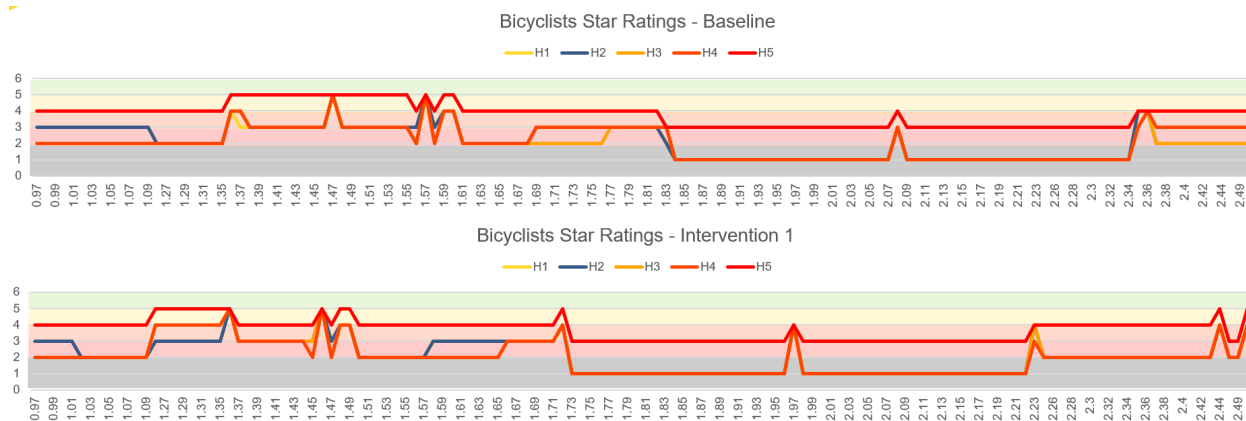


Figure 4-2 Dynamic Risk – Cyclists - Avenida del German Machado

#### Intervention 2 - Dynamic Risk – Pedestrians – Carrer del Doctor Manóel Candela

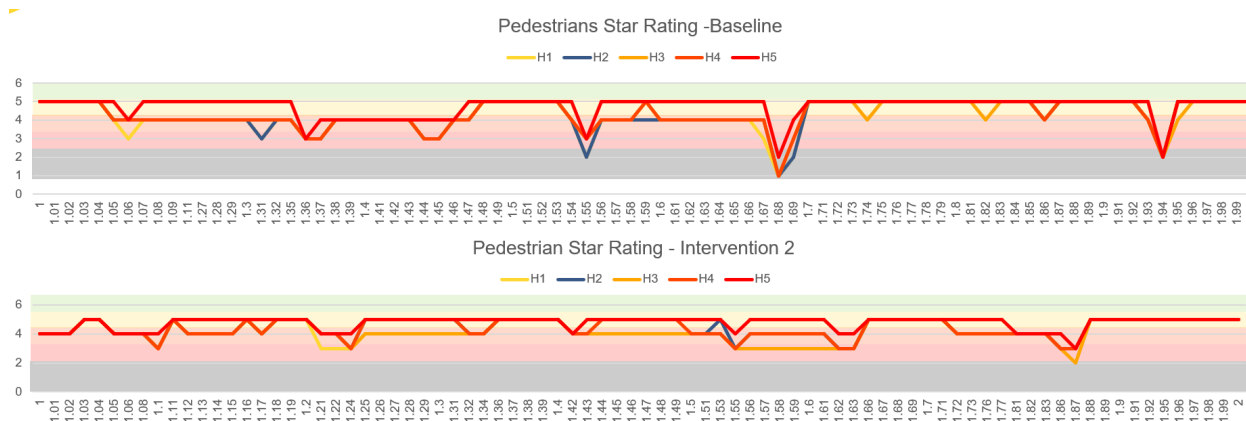


Figure 4-3 Dynamic Risk – Pedestrians – Carrer del Doctor Manóel Candela

#### Intervention 3 - Dynamic Risk – Bicyclists – Avenida dels Tarongers

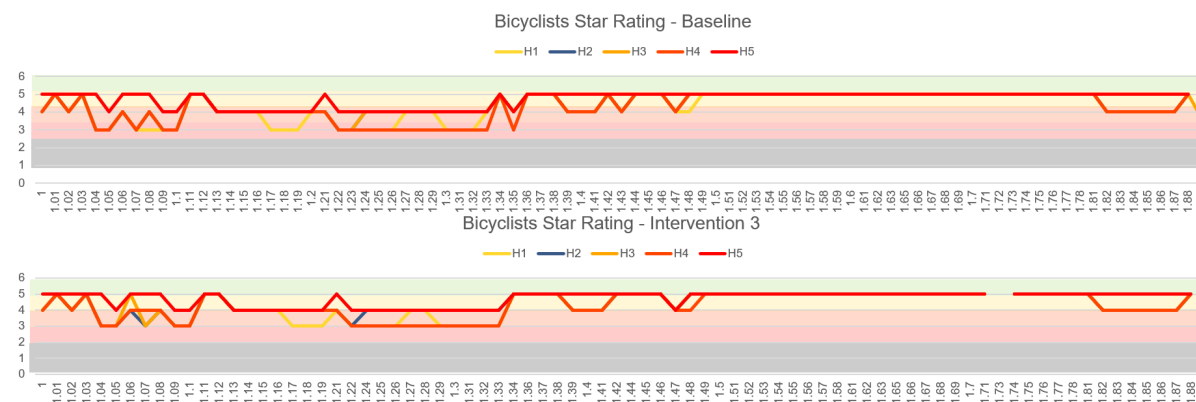


Figure 4-4 Dynamic Risk – Bicyclists – Avenida dels Tarongers





### Intervention 4 - Dynamic Risk – Pedestrians – Avenguda dels Tarongers

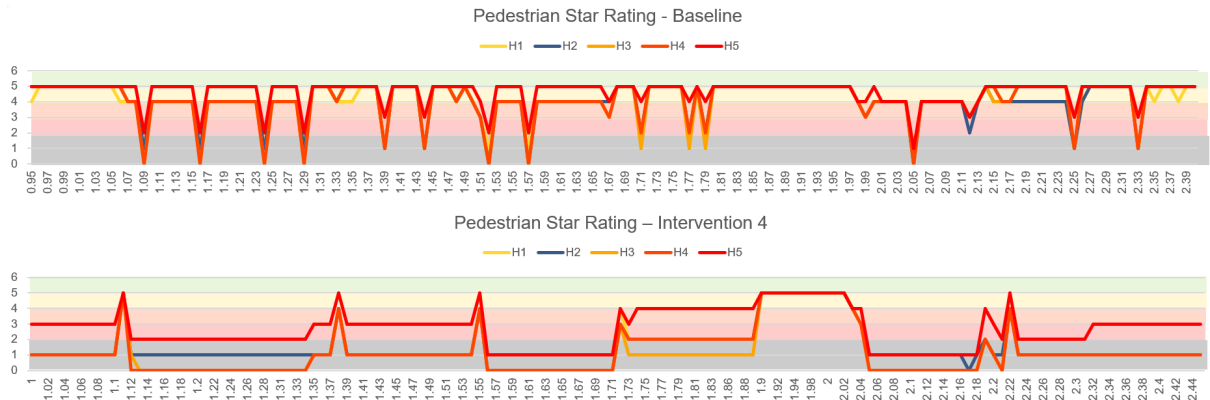


Figure 4-5 Dynamic Risk – Pedestrians – Avenguda dels Tarongers

#### 4.2.3. West Midlands

The demonstration of the application of the PHOEBE Framework in deliverable D3.2 will be based on two interventions:

- Intervention 1 evaluates the effects of removing the bicycle path established in A38.
- Intervention 2 tests the reduction of the speed limit from 40mph to 30mph on key roads.

The simulation consists of two model regions, comprised of 'Aimsun 1' and 'Aimsun 2', which cover 49 km<sup>2</sup> and 5 km<sup>2</sup>, respectively.

The model included five types of users: private cars, public transport, cyclists, shared micromobility, and pedestrians.

Simulations were carried out over several periods, such as during the morning peak, midday, and afternoon peak.

Simulation outputs were recorded across 15-minute time intervals throughout the simulation period. The needs of the experiment determined the choice of the Aimsun model region.

A total of four different experiments were modeled:

- Scenario 0 (baseline): representing conditions before any intervention implementation.
- Scenario 1: Active Travel - effect of introducing mode-specific routes.
- Scenario 2: Speed Limits - effect of reducing speed limits to 30 mph from 40 mph

Table 4-3 presents the results of the application of the PHOEBE framework in the form of the indicators. As presented in section 3.2, all the framework stages need to be completed to generate the indicators.

Table 4-3 Indicator results for WM

**Preliminary results. Results will be refined and validates in posterior tasks.**



| ID   | KPI Name                                                                        | Baseline<br>1 | Scenario<br>1 | Baseline<br>2 | Scenario<br>2 |
|------|---------------------------------------------------------------------------------|---------------|---------------|---------------|---------------|
| HS01 | Total number of fatalities and severe injuries on the network                   | 69            | 96            | 135           | 75            |
| HS02 | % of the network above road safety mark (3 stars or better) – Vehicle Occupant  | 100%          | 98%           | 2700          | 1491          |
| HS03 | % of the network above road safety mark (3 stars or better) – Motorcyclist      | 100%          | 98%           | 99%           | 97%           |
| HS04 | % of the network above road safety mark (3 stars or better) – Pedestrian        | 97%           | 93%           | 99%           | 95%           |
| HS05 | % of the network above road safety mark (3 stars or better) – Bicyclist         | 59%           | 35%           | 12%           | 0%            |
| HS06 | Risk variability within the simulated scenarios                                 | 0.031         | 0.042         | 4.171         | 4.493         |
| HS07 | Average road safety risk on nodes - Vehicle Occupant                            | 0.043         | 0.059         | 5.895         | 6.749         |
| HS08 | Average road safety risk on nodes - Motorcyclist                                | 0.285         | 0.444         | 356.727       | 272.775       |
| HS09 | Average road safety risk on nodes - Pedestrian                                  | 0.024         | 0.039         | 0.028         | 0.028         |
| HS10 | Average road safety risk on nodes - Bicyclists                                  | 1.736         | 2.493         | 6.428         | 4.901         |
| HS11 | Average road safety risk on links/sections - Vehicle Occupant                   | 2.040         | 2.932         | 7.931         | 6.043         |
| HS12 | Average road safety risk on links/sections - Motorcyclist                       | 5.970         | 9.246         | 339.258       | 222.639       |
| HS13 | Average road safety risk on links/sections - Pedestrian                         | 4.870         | 8.498         | 113.897       | 81.840        |
| HS14 | Average road safety risk on links/sections - Bicyclists                         | 45.92%        | 60.58%        | 4.171         | 4.493         |
| HS15 | % of the road network where the operating speed (85th) is above the speed limit | 0%            | 0%            | 24.9%         | 33.5%         |
| HS16 | % of road network with good quality sidewalk where operating speed (85th) is    | 0%            | 0%            | 0%            | 0%            |



| ID   | KPI Name                                                                                                                                | Baseline<br>1 | Scenario<br>1 | Baseline<br>2 | Scenario<br>2 |
|------|-----------------------------------------------------------------------------------------------------------------------------------------|---------------|---------------|---------------|---------------|
|      | over 30km/h or 20 mph, and a pedestrian is walking along the flow                                                                       |               |               |               |               |
| HS17 | % of road network with crossing facility where operating speed (85th) is over 30km/h or 20 mph, and there is a pedestrian crossing flow | 0%            | 0%            | 24.9%         | 33.5%         |
| HS18 | % of pedestrian crossings that are adequately signed and well-maintained                                                                | 0%            | 0%            | 0%            | 0%            |
| HS19 | % of road network with bicycle facility where operating speed (85th) is over 30km/h and there is bicyclist flow                         | 100%          | 98%           | 62%           | 61%           |
| OP01 | Network travel time (h)                                                                                                                 | 154.06        | 88.46         | 183.63        | 264.92        |
| OP02 | Network travel distance (km)                                                                                                            | 212466.43     | 211880.02     | 679234.03     | 669530.84     |
| OP03 | Network delay (s)                                                                                                                       | 51.95         | 44.44         | 30.19         | 30.68         |
| EN01 | Pollutant Emissions – CO2 (g)                                                                                                           | 36132918.95   | 35361255.10   | 100962871.62  | 103473896.88  |
| EN02 | Pollutant Emissions – NOx (g)                                                                                                           | 32890.93      | 32126.93      | 92120.75      | 92629.23      |

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### 4.2.3.1. Dynamic Risks Charts

Intervention 1 - Dynamic Risk – Bicyclists – A38

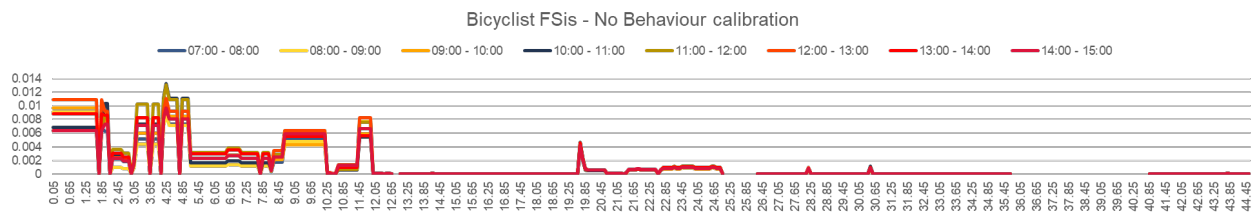


Figure 4-6 FSIs for WM Intervention 1 with no behaviour calibration



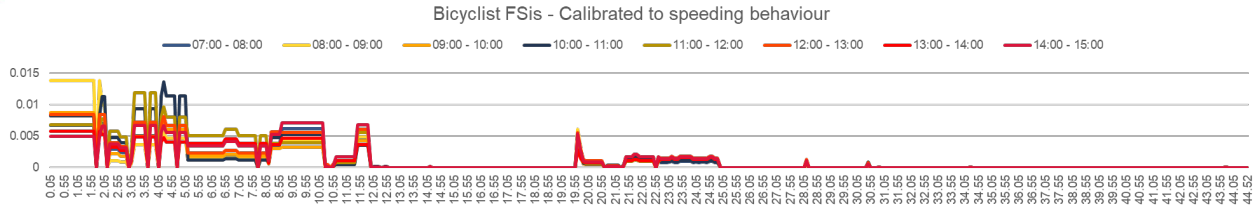


Figure 4-7 FSIs for WM Intervention 1 with behaviour calibration

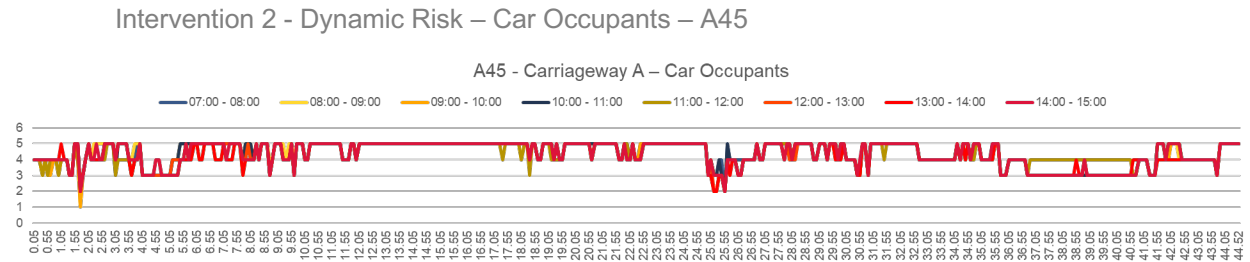


Figure 4-8 Baseline hourly risk for car occupants in the WM Intervention 2

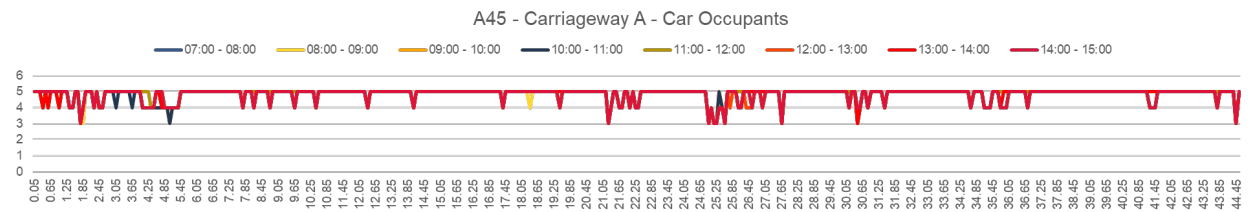


Figure 4-9 After hourly risk for car occupants in the WM Intervention 2

### 4.2.3.2. Additional analyses - Baseline results for before/after speeding behaviour model integration

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## 5. Conclusions

The completion of **Deliverable 3.2** marks a significant milestone in the PHOEBE project, encapsulating the development, refinement, and integration of various components within the PHOEBE framework. This chapter will summarise findings and describe how the Deliverable 3.2 achievements will feed future activities.

### 5.1. Delivered D3.2 Findings

**Deliverable 3.2** achieves its objectives by presenting the results framework for the pilot, the technical evaluation of the model enhancements and the final refinements conducted in the individual models for integration. The finalised version of the model are presented in the initial chapter followed by the completion of the use case demonstrations as the final enhancements produced and delivered in activities 3.1, 3.2, 3.3. and 3.4.

The findings and developments are presented in several key areas:

- **Mode Shift and Induced Demand Models:** These models estimated the safety impact of changes in urban mobility, focusing on mode shift, induced demand, and active travel behaviours. The models tailored for the use case application demonstrate the ability to estimate mode shift and induced demand impacts of interventions, giving special focus to the indicators that reinforce the non-motorised solutions.
- **Human Behaviour Models:** These models were developed and subsequently integrated into traffic microsimulation and road safety assessments, demonstrating the importance of considering integrated human factors and road user behaviours. They include discrete choice models for behaviours like speeding, red-light violations, and crossing outside designated areas, but more importantly, they establish a replicable framework for behaviour integration. The models also establish a crash-conflict relationship using Extreme Value Theory (EVT) to predict the number of crashes associated with each behaviour.
- **Risk Assessment Models:** The iRAP Star Rating PHOEBE enhancements allow for dynamic inputs, showing how safety varies throughout the day. By integrating traffic simulation data such as operating speeds and vehicle flows, the models now provide more detailed, consistent risk analysis, with plans for automation in later project stages.
- **Traffic Simulation Models:** Enhancements to the Aimsun simulation networks for the pilot cities include the integration of non-compliant behaviours and improvements on the mode shift integration. The deliverable also presented quick guidelines on how to connect the developed API and export the data needed for the subsequent stages.
- **Integration and Testing:** The document describes the integration of these components into the PHOEBE framework, the challenges encountered during the process, and the solutions implemented. It also highlights the progress made beyond the current state of the art and lists the indicators the framework can provide.

Overall, the findings demonstrate significant advancements in predictive safety assessment for urban environments, with a strong focus on VRUs and the integration of innovative modelling techniques and data sources.

This deliverable has successfully demonstrated the application of these components across the three use cases in Athens, Valencia, and the West Midlands, providing a robust foundation for assessing the impact of road safety dynamics on urban safety outcomes.



Throughout the project, the team has faced and overcome numerous technical challenges, showcasing the power of collaborative troubleshooting and innovative problem-solving.

## 5.2. Deliverable D3.2 impact on PHEOBE future activities

The insights gained from this deliverable will guide the development of the following steps, focusing on automatization, transferability, and scalability. The enhancements and developments conducted and presented as part of Deliverable D3.2, which enable the integration and operationalisation of the framework, will be translated into user-friendly guidelines to ensure the learnings serve as a blueprint for other European cities aiming to improve their urban safety frameworks, which will be developed under WP5.

*Table 5-1 Deliverable D3.2 impact on future project activities.*

| Deliverable D3.2                                      | Future project activities                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                              |
|-------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Demonstrations of the use cases                       | A thorough evaluation of use case outcomes is essential for driving progress within Work Package 4 (WP4). As innovative models and frameworks are tested in real urban environments, feedback and analysis from stakeholders—including city planners, transport authorities, community representatives, and technical experts—play a pivotal role. The evaluation will take place through a series of workshops and discussions focusing on the road networks and related topics. Findings from this collaborative process will be documented in Deliverable 4.2.                                                                                                                                                                                                                                                                                                      |
| Framework operationalisation                          | The lessons learned from the framework operationalisation trials conducted under WP3 will support the creation of user-friendly user guides. Through hands-on testing and evaluation in diverse city contexts, the project team has identified practical challenges, optimal workflows, and best practices for integrating the innovative modelling techniques and data sources developed in earlier phases. By systematically documenting the solutions to technical hurdles and the strategies that ensured reliable, scalable, and transferable application of the framework, these insights will be distilled into clear, actionable instructions for end users. This process will help transform complex methodologies into user-friendly steps, ensuring that other European cities can replicate and tailor the framework to their specific urban safety needs. |
| Internal flow data matrix and data processing demands | The internal flow matrix and data processing demands identified earlier in the project serve as the foundation for the optimization of data flows addressed under Task 5.4. By systematically analyzing these matrices—mapping how data moves between modules, partners, and use cases—project teams can pinpoint bottlenecks, redundancies, or gaps in the information exchange process. Additionally, understanding the specific demands of data processing support the optimization process, which may involve integrating advanced data management tools, developing robust validation and compliance checks, and adopting scalable architectures that can adapt to variable load.                                                                                                                                                                                 |
| Mode shift and induced demand enhancements            | The insights gleaned from modeling mode shift and induced demand are pivotal for enriching socioeconomic analysis. By closely examining how interventions influence travel behavior—such as encouraging shifts from private vehicles to public transport, cycling, or walking—these models provide a nuanced understanding of the cascading effects on congestion, accessibility, and overall urban mobility. In practical terms, the data generated by mode shift and induced demand modeling enables project teams to forecast changes in traffic patterns, anticipate new travel demands, and evaluate the redistribution of flows across the network. This information directly informs cost-                                                                                                                                                                      |



| Deliverable D3.2        | Future project activities                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  |
|-------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                         | benefit analyses by quantifying impacts on travel time, fuel consumption, emissions, and safety outcomes, all of which have significant economic and social implications. Moreover, the learnings help to identify potential equity concerns: for instance, whether certain groups benefit disproportionately from proposed changes or whether new demands may strain existing infrastructure in vulnerable areas. By integrating these findings into the socioeconomic evaluation, planners and stakeholders can craft strategies that not only maximize operational efficiency and safety but also promote inclusivity and resource allocation aligned with community needs.                                                                                                                                                                                                                                                                                                                             |
| Dynamic risk assessment | By enabling automatic data sharing between the dynamic risk assessment system (ViDA) and traffic simulation software (Aimsun Next), D3.2 will facilitate direct assessment of dynamic risk and intervention impacts. This data flow will ensure that T5.3 benefits from real-time risk analytics and robust simulation results, allowing stakeholders to assess interventions with greater accuracy and adapt strategies based on comprehensive, evidence-driven insights                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  |
| PHOEBE Indicators       | PHOEBE indicators play a key role in fostering both transferability and scalability, serving as a cornerstone for activities under T5.1 and T5.2. These indicators not only quantify economic impacts—such as reductions in congestion and improvements in safety—but also support comprehensive equity assessments and environmental evaluations. By embracing a data-driven approach, PHOEBE empowers stakeholders to prioritize interventions that yield measurable benefits and ensures that socio-economic analyses encompass the full spectrum of impacts, including safety alongside operational criteria in cost-benefit assessments. Furthermore, PHOEBE’s adaptable indicators extend their utility beyond the boundaries of individual cities, laying the groundwork for safety enhancements across Europe. The indicators developed for PHOEBE use cases will be systematically reevaluated for their applicability and effectiveness in diverse European contexts, as envisioned in Task 5.1. |

The successful demonstration of interventions per use case highlights the practical applicability of the developed models and their potential to drive positive change in urban environments.

### Data – From absence to overload.

Data plays a fundamental role for PHOEBE. It is utilized in three key stages: model development, model application, and calibration/validation. It may originate from sources both internal and external to the project. Accessing, complying with requirements, and processing data can indeed pose challenges to the reapplication of PHOEBE. Project partners have made a concerted effort to map the competitive data sources and their applicability. Guidelines on how to handle data within the framework will support user documentation in future stages of the project.

### Flexibility is key for Adaptability.

The beauty of the PHOEBE framework lies in its flexibility, allowing cities to implement it based on their unique expertise, resources, and interests. Unlike rigid frameworks that require a step-by-step approach from start to finish, PHOEBE can be adapted to suit the specific needs and priorities of each city. This means that cities can choose which components to apply, such as traffic simulation, road safety assessment, human behaviour modelling, or mode shift and induced demand modelling.





### Light at the end of the tunnel

The PHOEBE project still has a long way to go to ensure the results are appropriate and meet stakeholders' expectations. Continuous refinement of the models is essential, incorporating feedback from stakeholders to address any gaps or areas for improvement. Additionally, generating comprehensive user guides for stakeholders is crucial to ensure they can effectively utilize the new systems and tools developed as part of the project. These guides will provide clear instructions and best practices, enabling stakeholders to maximize the benefits of the project and contribute to its overall success.

## 6. References

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Konstantinos A. Apostoleris, Stella N. Sarma, Trakakis E. Antonios, Psarianos Basil (2023) Traffic Speed Variability as an Indicator of the Provided Road Safety Level in Two-Lane Rural Highways. Transportation Research Procedia Volume 69, 2023, Pages 241-248. DOI: [10.1016/j.trpro.2023.02.168](https://doi.org/10.1016/j.trpro.2023.02.168)

Panick Kalambay & Srinivas S. Pulugurtha (2024) Data-driven exploration of traffic speed patterns to identify potential road links for variable speed limit sign implementation, *Urban, Planning and Transport Research*, 12:1, 2319711, DOI: [10.1080/21650020.2024.2319711](https://doi.org/10.1080/21650020.2024.2319711)



# A. Appendixes

## A.1 Demand model surveys and induced demand results

Survey design:

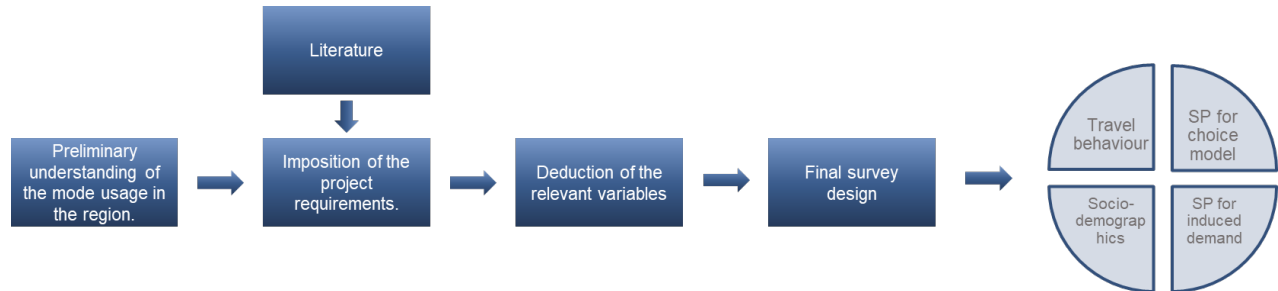


Figure A-1 Survey design

Characteristics:

- The surveys for all the use cases were representative of the age and gender
- A total of 500 samples were considered in all the use cases
- Total # of mode choice responses planned = 8 (scenarios) x 500 (samples) = 4,000
- Total # of induced demand responses planned = 4 (scenarios) x 500 (samples) = 2,000

Parts of the survey:

1. Travel behaviour (revealed)
2. Stated preference for the mode choice with 8 scenarios/respondent (D-Efficient design)
3. Stated preference for the induced demand with 4 scenarios/respondent (Orthogonal design)
4. Socio-demographics

Variables considered in the travel behaviour section:

- Driving license ownership
- Car availability
- Public transport pass availability
- Micro-mobility usage
- Current trip-making behaviour
- Mode usage (revealed)
- Travel attitudes
- Crashes and their types in the last year

Variables considered: D-Efficient design using software **NGENE**

Modes (as alternatives)

- WM: Car, Public transport, Private bike, Shared micro-mobility, Walk, None (opt-out)



### 3.2 – Finalized models/simulation environments, methodology factsheets and users support materials

- VLC: Car, Public transport, Private micro-mobility, Shared micro-mobility, Walk, None (opt-out)
- ATH: Car, Public transport, Motorcycle, Shared micro-mobility, Walk, None (opt-out)

#### Attributes and levels

- Travel cost [+30%, 0%, -30%]
- Door-to-door time (In-vehicle time [+30%, 0, -30%] + Access-Wait-Egress time [+30%, 0, -30%])
- Access-Wait-Egress time [+30%, 0, -30%]
- The risk is involved. Public transport (found safest) [+30%, 0, -30%]

#### Scenarios

- Trip distances: 2 KM (1.2 Miles) and 5 KM (3.1 Miles)
- Trip purpose: Commute, shopping, and leisure
- Condition during the trip: Daytime, Night + Light, Night + Dark (without light)

#### Stated Preference – Risk Calculation

- The risks associated with the modes shown on the SP survey cards are relative to Public Transport.
- Public transport is found to be the safest among all the modes in all the use cases.
- For the survey, “Relative Risk” is used where the risk associated with the modes is normalised relative to the risk associated with PT.

#### Calculation. Example – West Midlands

Table A-1 Historical crash data

| Crash data (2022)                   | Car      | PT       | SMM      | Private MM | Walk     |
|-------------------------------------|----------|----------|----------|------------|----------|
| Killed                              | 1331     | 48       | 14       | 94         | 385      |
| Serious injury/crash                | 15425    | 1432     | 313      | 3531       | 3969     |
| Light injury/crash                  | 58184    | 5401     | 1179     | 13318      | 14973    |
| Total fatalities weighted with FWI  | 3164     | 218      | 51       | 514        | 857      |
| Total TripKM                        | 4.58E+11 | 8.19E+10 | 6.81E+08 | 5.89E+09   | 3.28E+10 |
| FWI weighted fatalities/1000 TripKM | 6.91E-06 | 2.66E-06 | 7.52E-05 | 8.72E-05   | 2.61E-05 |
|                                     |          | Minimum  |          |            |          |
| Relative risk (shown in the survey) | 3        | 1        | 28       | 33         | 10       |



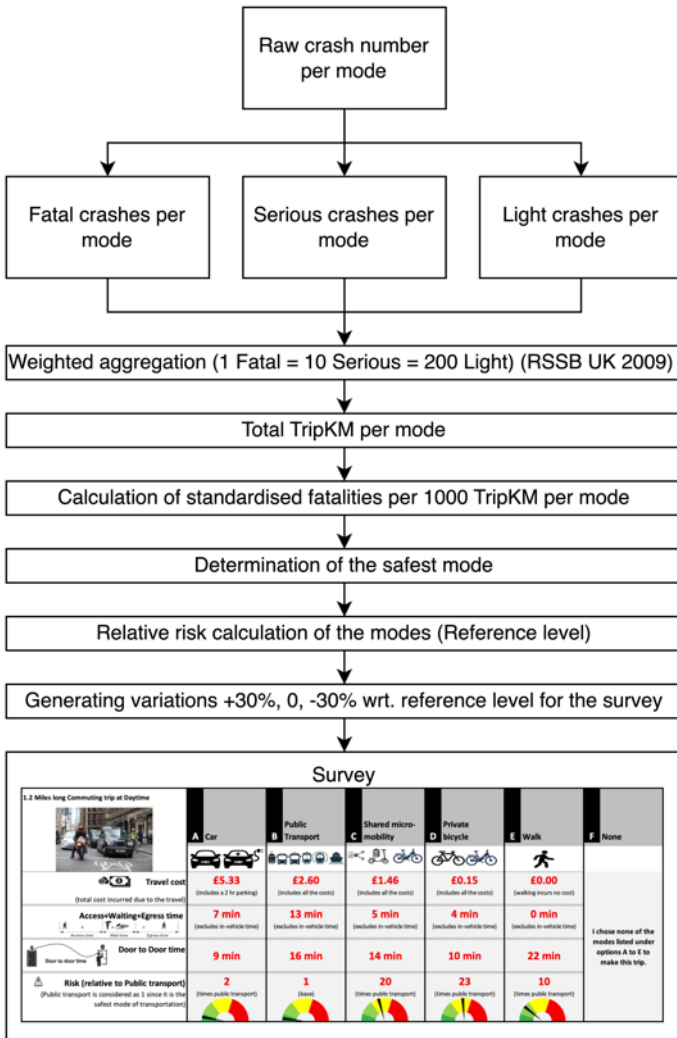


Figure A-2 Risk calculations for the demand survey

#### Predictors

To develop the mode choice model, the following variables are considered:

- Travel cost (monetary)
- In-Vehicle time
- Access-Wait-Egress time
- Risk (associated with the modes wrt. PT)
- Trip length
- Age
- Gender

To develop the induced demand model (micro-mobility), the following variables are considered:

- Difference in travel cost (monetary)



- Difference in In-Vehicle time
- Difference in Access-Wait-Egress time
- Difference in Risk (associated with the modes wrt. PT)
- Trip length
- Age
- Gender

Any changes/interventions will change the predictors affecting the mode choice and induced demand.

### Example of the Stated Preference – Mode choice

\*Consider making a **1.2-mile-long commuting trip** (e.g., Work and/or education trip) **during the daytime**.

Based on the Travel Cost (£), Access + Wait + Egress Time (min), Door to Door Time (min) and Risk Associated (relative to Public Transport) for the options listed below,

| 1.2 Miles long Commuting trip at Daytime                                                                                                                                                                             |                                           |                                          |                                          |                                          |                                          |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------|------------------------------------------|------------------------------------------|------------------------------------------|------------------------------------------|
|                                                                                                                                                                                                                      | A Car                                     | B Public Transport                       | C Shared micro-mobility                  | D Private bicycle                        | E Walk                                   |
|  <b>Travel cost</b><br>(total cost incurred due to the travel)                                                                      | <b>£5.33</b><br>(includes a 2 hr parking) | <b>£2.60</b><br>(includes all the costs) | <b>£1.46</b><br>(includes all the costs) | <b>£0.15</b><br>(includes all the costs) | <b>£0.00</b><br>(walking incurs no cost) |
|  <b>Access+Waiting+Egress time</b><br>(excludes in-vehicle time)                                                                    | <b>7 min</b>                              | <b>13 min</b>                            | <b>5 min</b>                             | <b>4 min</b>                             | <b>0 min</b>                             |
|  <b>Door to Door time</b>                                                                                                           | <b>9 min</b>                              | <b>16 min</b>                            | <b>14 min</b>                            | <b>10 min</b>                            | <b>22 min</b>                            |
|  <b>Risk (relative to Public transport)</b><br>(Public transport is considered as 1 since it is the safest mode of transportation) | <b>2</b><br>(times public transport)      | <b>1</b><br>(base)                       | <b>20</b><br>(times public transport)    | <b>23</b><br>(times public transport)    | <b>10</b><br>(times public transport)    |
| I chose none of the modes listed under options A to E to make this trip.                                                                                                                                             |                                           |                                          |                                          |                                          |                                          |

which option would you choose to make this trip?

Choose one of the following answers

- ☐ A) Car
 ☐ B) Public transport
 ☐ C) Shared micro-mobility
 ☐ D) Private bicycle
 ☐ E) Walk
 ☐ F) None

Figure A-3 Example of the Stated Preference – Mode choice

### Variables considered (Induced demand only for shared micro-mobility): Orthogonal design

Alternatives (for all use cases)

- 2 more trips/week
- 1 more trip/week
- No change
- 1 less trip/week
- 2 or less trips/week
- None (Opt-out)

Attributes and levels

- Difference in travel cost [+25%, 0%, -30%]

## 3.2 – Finalized models/simulation environments, methodology factsheets and users support materials

- Difference in door-to-door time (In-vehicle time [+25%, 0, -30%] + Access-Wait-Egress time [+25%, 0, -30%])
- Difference in access-Wait-Egress time [+25%, 0, -30%]
- Difference in the risk involved with respect. Public transport (found safest) [+25%, 0, -30%]

### Scenarios

- Trip distances: 2 KM (1.2 Miles) and 5 KM (3.1 Miles)
- Trip purpose: Commute, shopping, and leisure
- Condition during the trip: Daytime, Night + Light, Night + Dark (without light)

\* Εξετάστε το ενδεχόμενο να πραγματοποιήσετε μια μεγάλη διαδρομή 2 χιλιόμετρα (π.χ. μετακίνηση για εργασία ή/και εκπαίδευση) κατά τη διάρκεια της ημέρας με κοινόχρηστο τρόπο μικρο-κινητικότητας.

| 2 KM μεγάλη διαδρομή (π.χ. εργασία, εκπαίδευση) κατά τη διάρκεια της ημέρας                                                                              |                                                                   |                                                                   |                                        |
|----------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|-------------------------------------------------------------------|----------------------------------------|
|                                                                                                                                                          | A Τρέχουσα αξία                                                   | B Νέα αξία                                                        | C Ποσοστιαία μεταβολή                  |
| <b>Κόστος διαδρομής</b><br>(συνολικό κόστος της διαδρομής)                                                                                               | 2.50 €<br>(περιλαμβάνει όλα τα έξοδα)                             | 1.75 €<br>(περιλαμβάνει όλα τα έξοδα)                             | -30%<br>(μείωση από την τρέχουσα αξία) |
| <b>Χρόνος πρόσβασης + αναμονής + εξόδου</b><br>(εξαιρείται ο χρόνος μέσα στο όχημα)                                                                      | 4 λεπτά                                                           | 3 λεπτά                                                           | -30%<br>(μείωση από την τρέχουσα αξία) |
| <b>Χρόνος πόρτα-πόρτα</b>                                                                                                                                | 14 λεπτά                                                          | 10 λεπτά                                                          | -30%<br>(μείωση από την τρέχουσα αξία) |
| <b>Κίνδυνος (σε σχέση με τις δημόσιες μεταφορές)</b><br>(Τα μέσα μαζικής μεταφοράς θεωρούνται ως 1, δεδομένου ότι είναι ο ασφαλέστερος τρόπος μεταφοράς) | 82<br>(πολλαπλασιασμός της αξίας κινδύνου των δημόσιων μεταφορών) | 57<br>(πολλαπλασιασμός της αξίας κινδύνου των δημόσιων μεταφορών) | -30%<br>(μείωση από την τρέχουσα αξία) |

Πώς αυτές οι αλλαγές στο κόστος διαδρομής (€), στους χρόνους (λεπτά) και στο προφίλ κινδύνου θα επηρεάσουν την εβδομαδιαία συχνότητα πραγματοποίησης μετακινήσεων σας με το κοινόχρηστο μέσο μικρο-κινητικότητας;

#### Επιλέξτε μια από τις παρακάτω απαντήσεις

- ☐ Α) Θα κάνω δύο λιγότερες μετακινήσεις/εβδομάδα με κοινόχρηστη μικρο-κινητικότητα.
 ☐ Γ) Δεν θα κάνω καμία αλλαγή.
 ☐ Ε) Θα κάνω δύο επιπλέον διαδρομές/εβδομάδα με κοινόχρηστη μικρο-κινητικότητα.
- ☐ Β) Θα κάνω μια λιγότερη μετακίνηση/εβδομάδα με κοινόχρηστη μικρο-κινητικότητα.
 ☐ Δ) Θα κάνω μια επιπλέον διαδρομή/εβδομάδα με κοινόχρηστη μικρο-κινητικότητα.
 ☐ ΣΤ) Τίποτα από τα παραπάνω

Figure A-4 Example in Greek Stated Preference – Induced demand for the Athens survey

## A.2 Demand Surveys results

Athens (EL) [n = 501 respondents]

| Quota        | Prescribed | Relative    | Achieved   | Relative    | Difference |
|--------------|------------|-------------|------------|-------------|------------|
| Age 0-17     | 0          | 0%          | 0          | 0%          | 0%         |
| Age 18-24    | 38         | 8%          | 38         | 8%          | 0%         |
| Age 25-34    | 93         | 19%         | 96         | 19%         | 0%         |
| Age 35-44    | 97         | 19%         | 122        | 24%         | 5%         |
| Age 45-54    | 85         | 17%         | 110        | 22%         | 5%         |
| Age 55-69    | 103        | 21%         | 120        | 24%         | 3%         |
| Age 70+      | 83         | 17%         | 15         | 3%          | -14%       |
| <b>Total</b> | <b>500</b> | <b>100%</b> | <b>501</b> | <b>100%</b> | <b>500</b> |
| Female       | 261        | 52%         | 261        | 52%         |            |
| Male         | 239        | 48%         | 240        | 48%         |            |
| <b>Total</b> | <b>500</b> | <b>100%</b> | <b>501</b> | <b>100%</b> |            |

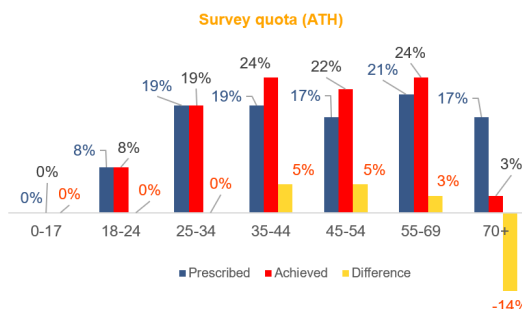


Figure A-5 Athens's survey quota.

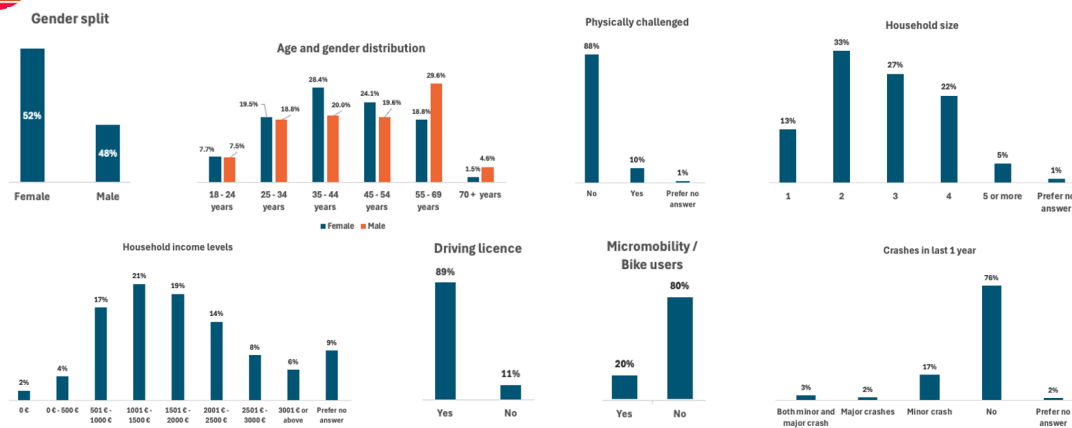


Figure A-6 Athens's socio-demographics & travel behaviour.

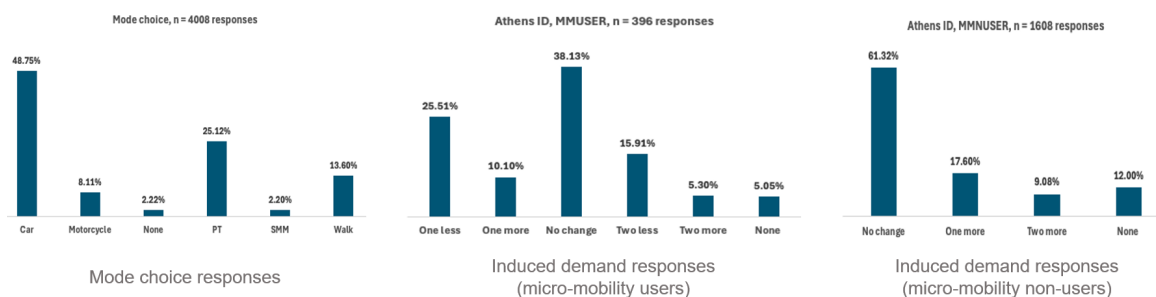


Figure A-7 Athens' stated preferences

Athens (EL) [n = 501 respondents]

- Designed time of the survey: 20-25 min
- Median completion time: 12.34 min
- Mean completion time: 17.11 min
- # Lexicographic responses (MC): 824 responses
- Variables with endogeneity:

| Variable                | Modes               | Instrumental variables                    |
|-------------------------|---------------------|-------------------------------------------|
| Travel cost             | Car, PT, Bike       | Trip distance, Time of trip               |
| In-Vehicle Time         | Car, PT, Bike, Walk | Trip distance, Time of trip               |
| Risk                    | Car, Bike, Walk     | Trip distance, Time of trip, Trip purpose |
| Access-Wait-Egress Time | Car, PT, Bike       | Trip distance, Time of trip               |

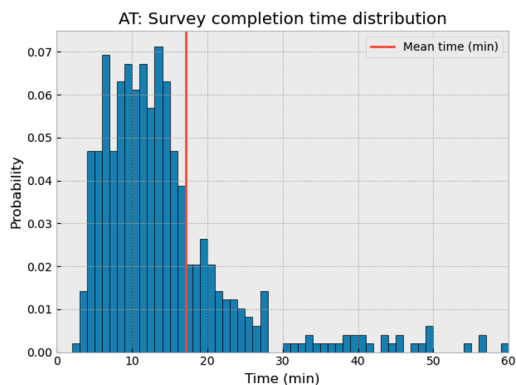


Figure A-8 Athens's survey completion time distribution.

| Quota        | Prescribed | Relative    | Achieved   | Difference |
|--------------|------------|-------------|------------|------------|
| Age 0-17     | 0          | 0%          | 0          | 0%         |
| Age 18-24    | 55         | 11%         | 55         | 0%         |
| Age 25-34    | 89         | 18%         | 89         | 0%         |
| Age 35-44    | 101        | 20%         | 101        | 0%         |
| Age 45-54    | 116        | 23%         | 116        | 0%         |
| Age 55-69    | 105        | 21%         | 105        | 0%         |
| Age 70+      | 35         | 7%          | 34         | 0%         |
| <b>Total</b> | <b>500</b> | <b>100%</b> | <b>500</b> | <b>500</b> |
| Female       | 258        | 52%         | 258        | 0%         |
| Male         | 242        | 48%         | 242        | 0%         |
| <b>Total</b> | <b>500</b> | <b>100%</b> | <b>500</b> | <b>500</b> |

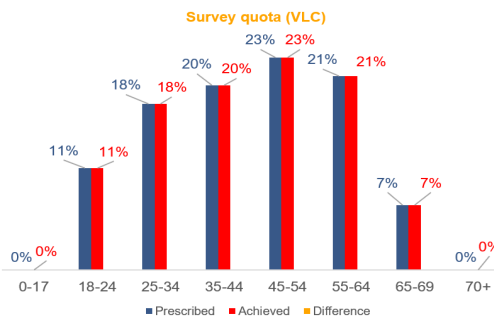


Figure A-9 Valencia survey quota.



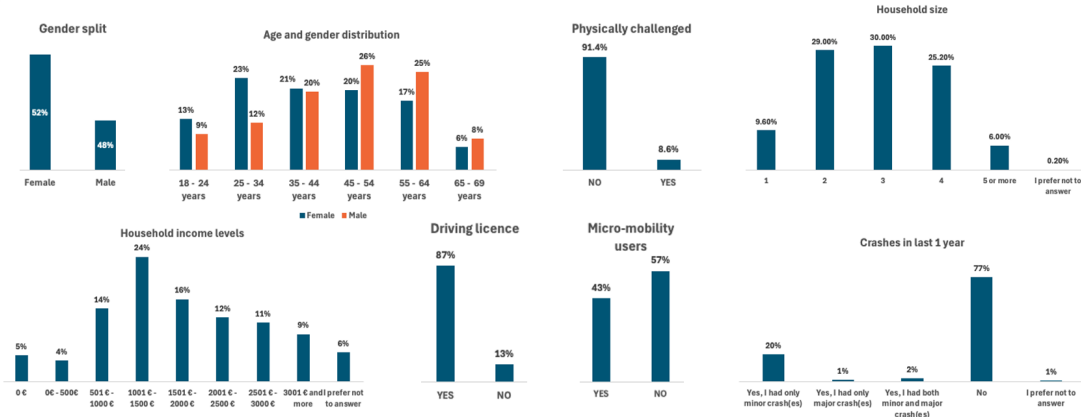


Figure A-10 Valencia Socio-demographics & Travel behaviour.

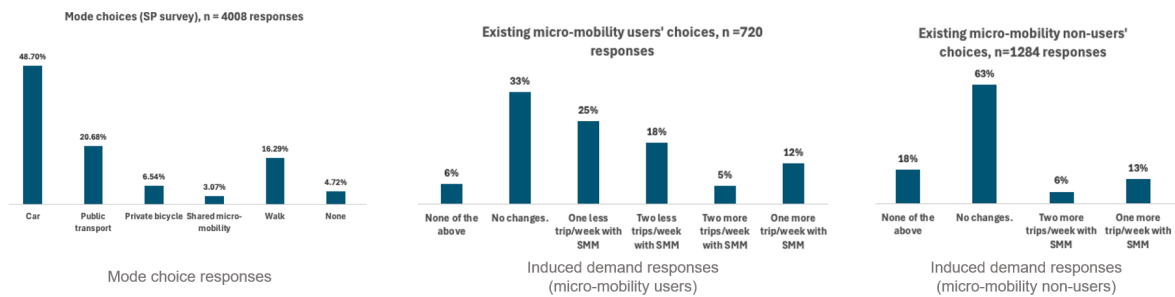


Figure A-11 Valencia stated preferences.

Valencia (ES) [n = 500 respondents]

- Designed time of the survey: 20-25 min
- Median completion time: 11.71 min
- Mean completion time: 17.28 min
- # Lexicographic responses (MC): 656 responses
- Variables with endogeneity:

| Variable                | Modes               | Instrumental variables                    |
|-------------------------|---------------------|-------------------------------------------|
| Travel cost             | Car, PT, Bike       | Trip distance, Time of trip               |
| In-Vehicle Time         | Car, PT, Bike, Walk | Trip distance, Time of trip               |
| Risk                    | Car, Bike, Walk     | Trip distance, Time of trip, Trip purpose |
| Access-Wait-Egress Time | Car, PT, Bike       | Trip distance, Time of trip               |

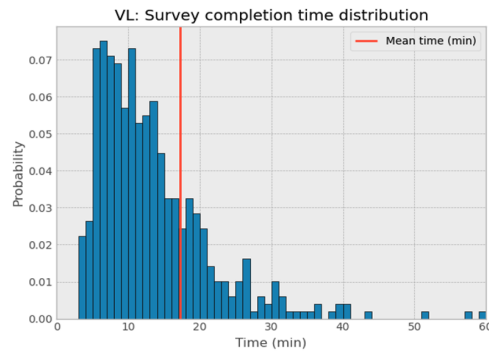


Figure A-12 Valencia Survey completion time distribution.

West Midlands (UK) [n = 501 respondents]

| Quota        | Prescribed | Relative    | Achieved   | Difference |
|--------------|------------|-------------|------------|------------|
| Age 0-17     | 0          | 0%          | 0          | 0%         |
| Age 18-24    | 67         | 13%         | 67         | 0%         |
| Age 25-34    | 103        | 21%         | 103        | 0%         |
| Age 35-44    | 98         | 20%         | 98         | 0%         |
| Age 45-54    | 103        | 21%         | 103        | 0%         |
| Age 55-69    | 130        | 26%         | 130        | 0%         |
| Age 70+      | 0          | 0%          | 0          | 0%         |
| <b>Total</b> | <b>501</b> | <b>100%</b> | <b>501</b> | <b>0%</b>  |
| Female       | 252        | 50.3%       | 252        | 0%         |
| Male         | 249        | 49.7%       | 249        | 0%         |
| <b>Total</b> | <b>501</b> | <b>100%</b> | <b>501</b> | <b>0%</b>  |

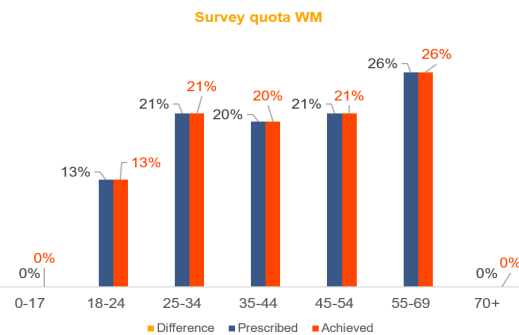


Figure A-13 WM survey quota.

## 3.2 – Finalized models/simulation environments, methodology factsheets and users support materials

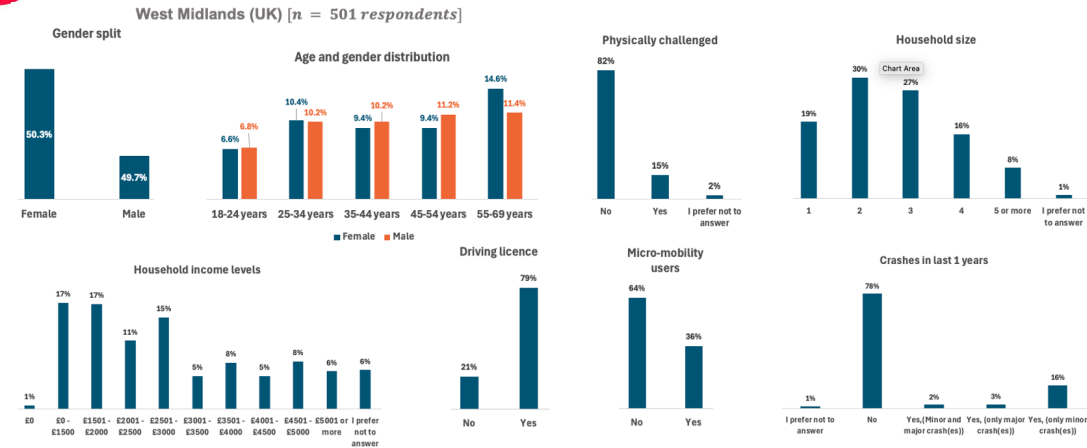


Figure A-14 WM Socio-demographics & Travel behaviour.

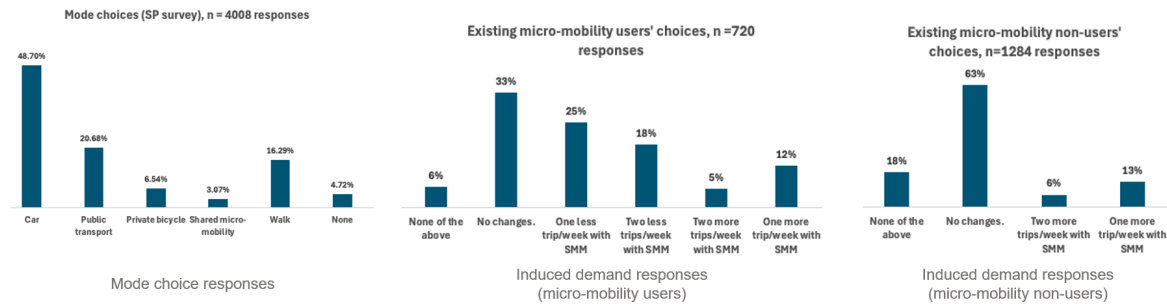


Figure A-15 WM Stated preference.

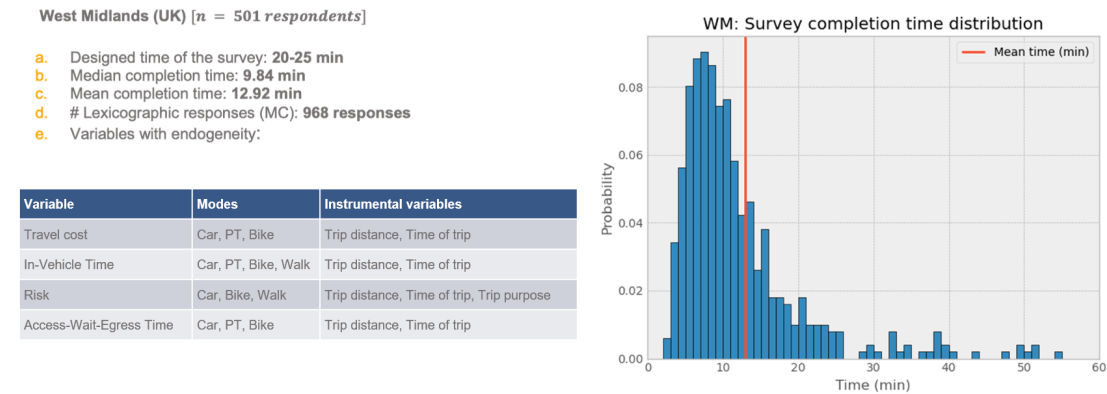


Figure A-16 WM Survey completion time distribution



## A.3 Behavioural survey procedures within PHOEBE

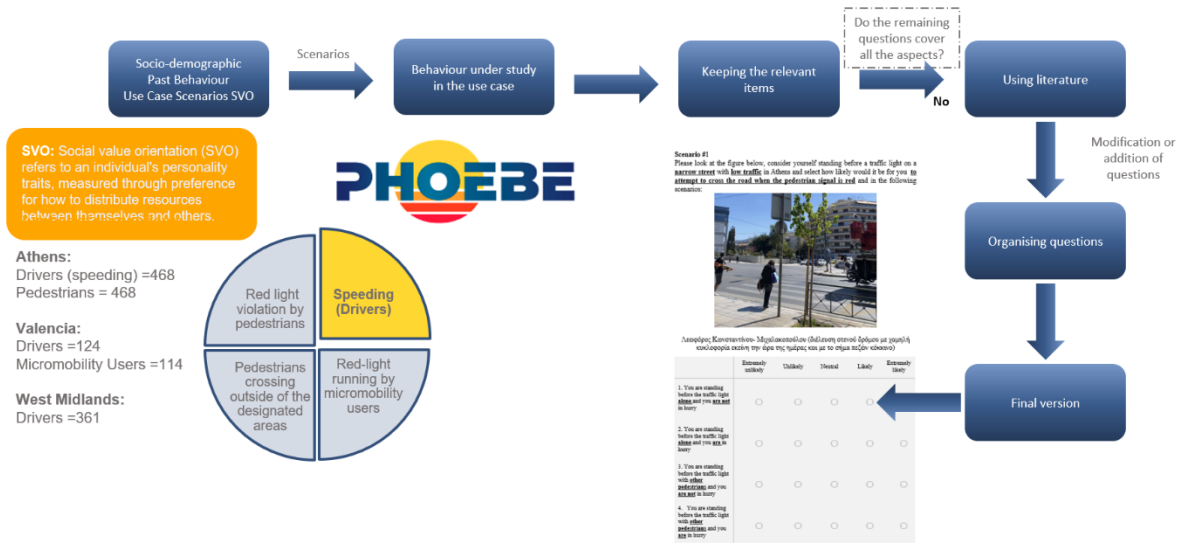


Figure A-17 Behavioural survey procedure

## A.4 Risk Assessment Model – Testing FSI's calibration factor for speeding behaviour

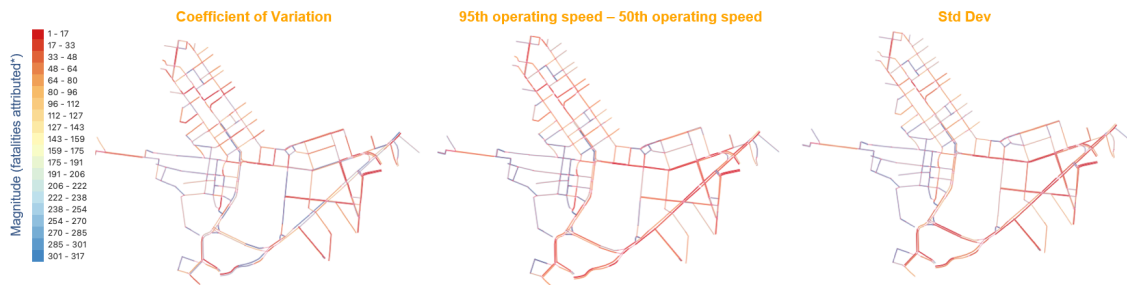


Figure A-18 Athens Testing FSI's calibration factor for speeding behaviour.

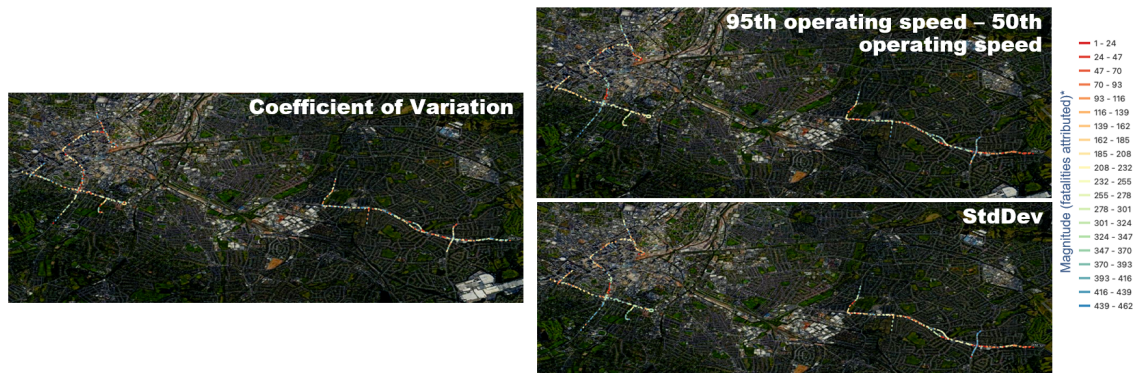


Figure A-19 WM Testing FSI's calibration factor for speeding behaviour

### A.5 Risk Assessment Model – CycleRAP FSIs

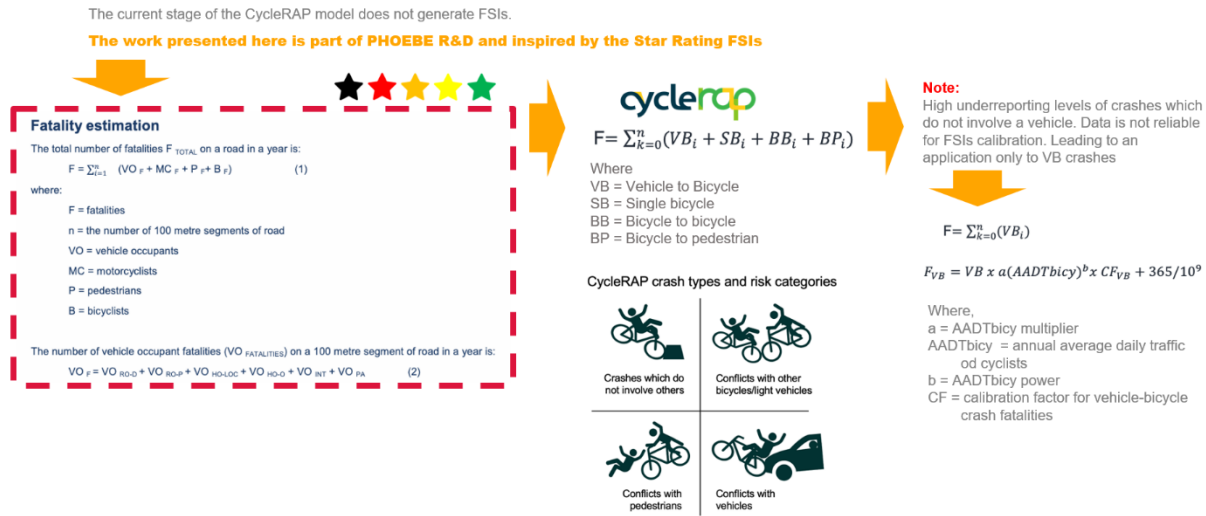


Figure A-20 CycleRAP FSIs calculations background.

The current stage of the CycleRAP model does not generate FSIs.

**The work presented here is part of PHOEBE R&D and inspired in the Star Rating FSIs**

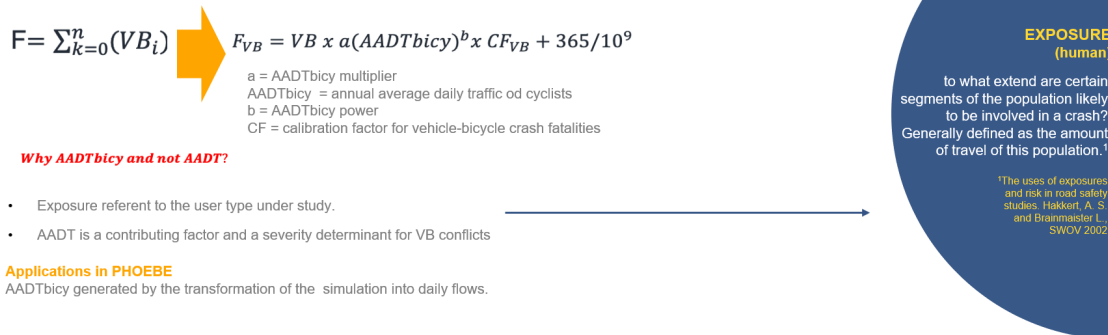


Figure A-21 CycleRAP FSIs equations

### A.6 Risk assessment validation form results

The charts in Figure A-22 present the combined feedback results for the three use cases: Athens, Valencia, and West Midlands. The low or very low reports were carefully reviewed and discussed with the use case leaders to identify improvements, make changes in the static coding, or clarify questions on the results.



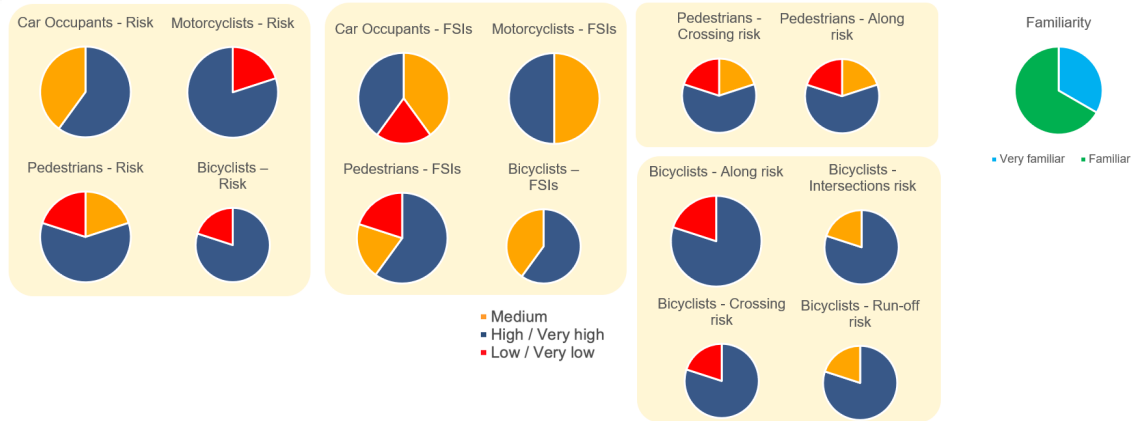


Figure A-22 Risk Assessment Model - Results From the Validation Form

## A.7 Demonstration of behaviours inside AIMSUN Next Software

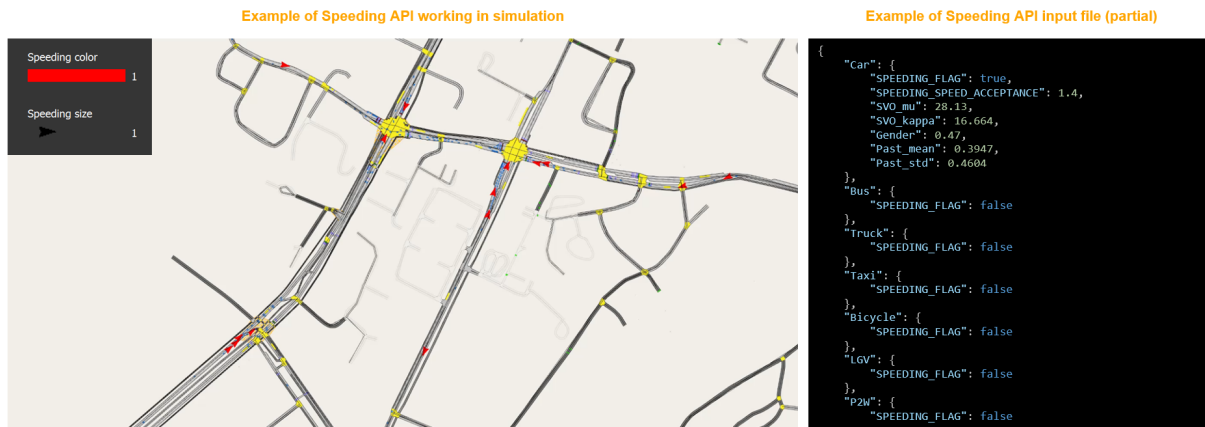


Figure A-23 Demonstration of behaviours – Speeding.

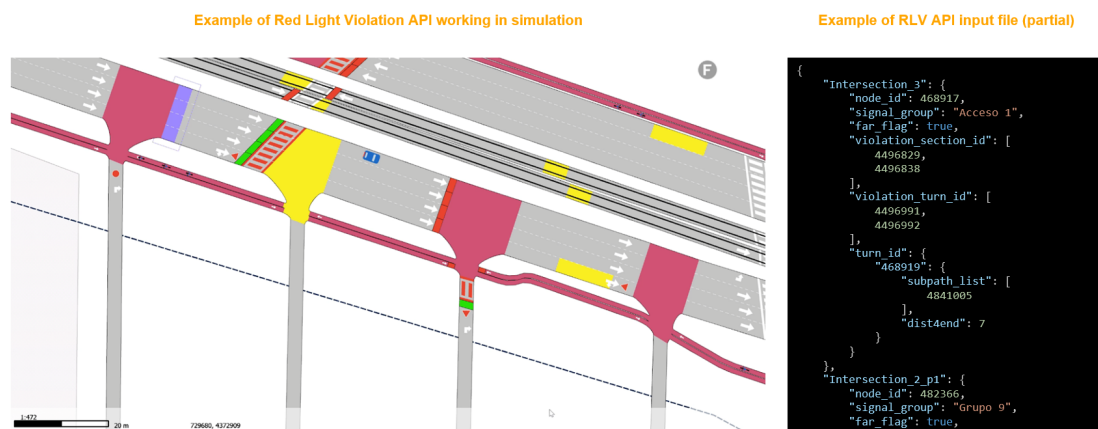


Figure A-24 Demonstration of behaviours – Red-light violation for micromobility

Detail of a pedestrian crossing with the waiting areas in the simulation

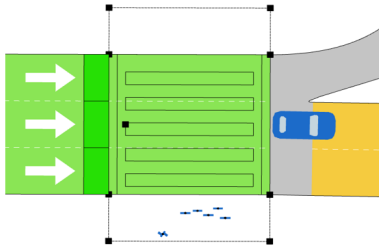


Figure A-25 Demonstration of behaviours – Red-light violation for pedestrians

## A.8 Instructions on how to perform simulations in the AIMSUN Next Software

### Simulation Dedicated Workflow

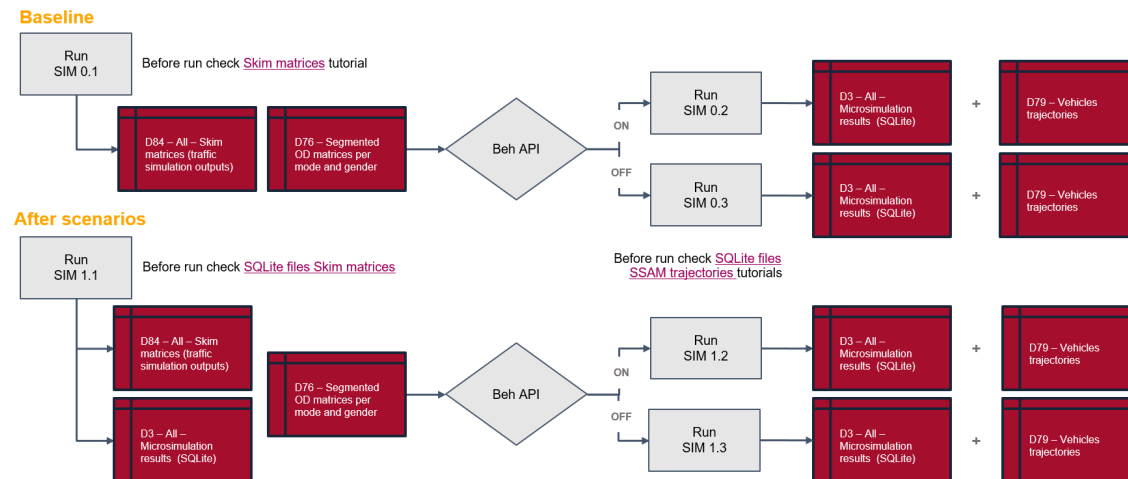


Figure A-26 Simulation dedicated workflow

### How to Set Up the Extraction of the CO2 Emissions (I)

Instructions on the LEM model: [Vehicle Types - Aimsun Next Users Manual](#) (Aimsun, 2025).

1. For each vehicle type, you need to set the fleet composition.
2. This is done at PROJECT -> DEMAND DATA -> Vehicles
3. Make sure that you introduce Euro values for Petrol and Diesel

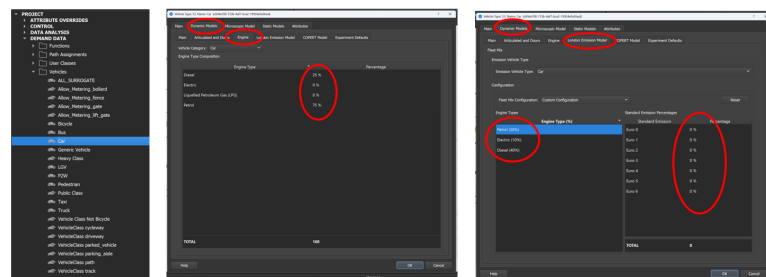


Figure A-27 LEM model – Setting petrol values.



- On the scenario, mark the outputs to be stored in the SQLite Database.

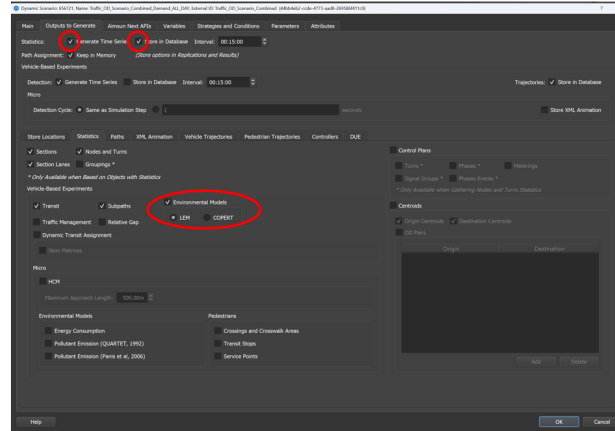


Figure A-28 LEM model - Selection of outputs.

### Risk Assessment SQLite Needs

Store the SQLite database with statistics gathered every 15 minutes for Sections, Nodes, Turns, and Section Lanes

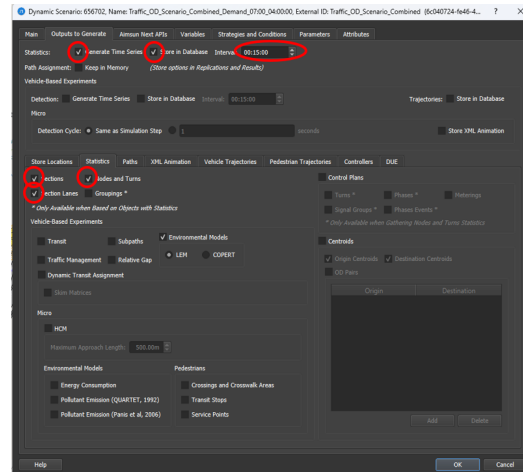
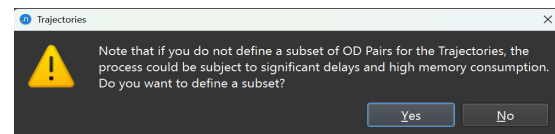


Figure A-29 SQLite Selection of outputs.

### SQLite Trajectories Vehicles

- In the scenario, mark the trajectories to be saved.
- Make sure that "All" OD Pairs are selected if not, click add.
- When doing that and exiting the scenario, a warning will appear. Click No





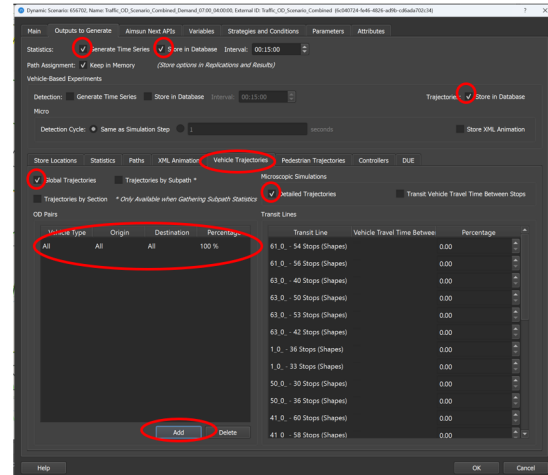


Figure A-30 Selecting the SQLite trajectories.

### SQLite Trajectories Pedestrians

1. In the scenario, mark the trajectories to be saved.
2. Make sure that "All" OD Pairs are selected if not, click add.
3. When doing that and exiting the scenario, a warning will appear. Click No

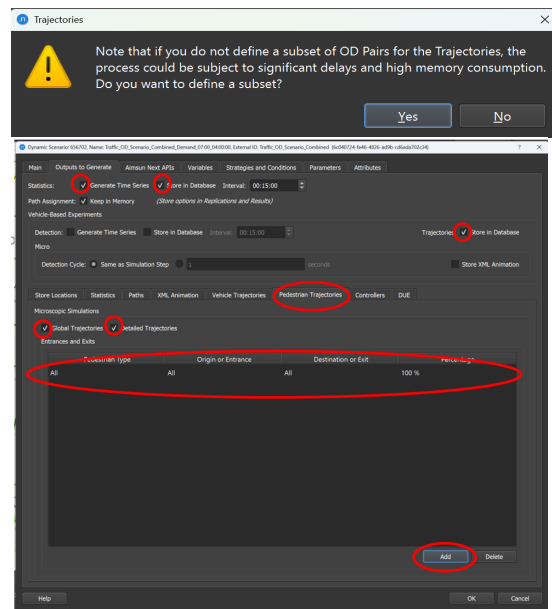


Figure A-31 Selecting the SQLite trajectories.

### SSAM (\*.trj) Trajectories

To save the .trj file, follow the following steps.

1. Double-click the dynamic scenario you want to run - a window will open as shown in the figure on the right.
2. Under the window, go to the Aimsun Next API tab
3. Under the simulation extensions, check the box for SSAM
4. By double-clicking the SSAM option, you can name the output file according to your preferences for different scenarios (e.g., with and without API).

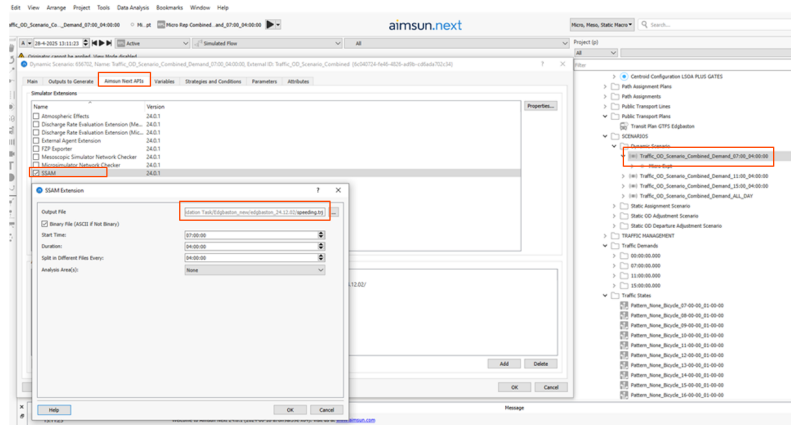


Figure A-32 Process to save TRJ files.

### Scripts into AIMSUN

#### Prerequisites

- Have Aimsun Next installed
- Have the Python module pandas available in Aimsun
- Have the simulation network
- Have the code “post\_run\_skim\_matrices\_25\_04\_10.py”
- Have an Aimsun version from April 2025 onwards.
- Installers can be found upon request

#### Add the Script into Aimsun

1. The script is added as a post-run script, so it is automatically executed at the end of the simulation.
2. Right click on scripts -> New Python script
3. Select Pre-run or Post-Run Script
4. A new script has appeared; double-click it
5. A new window opens. You can change the script name to a one you like, for instance, export skim matrices.

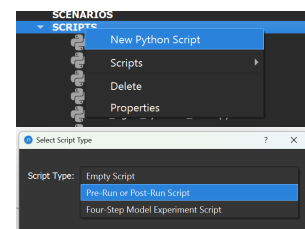


Figure A-33 Adding new scripts.

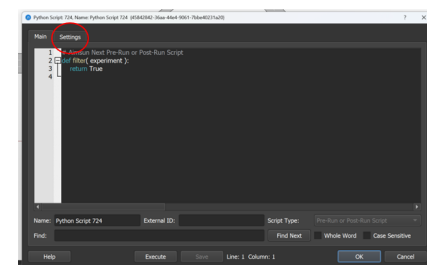


Figure A-34 Renaming script.

6. Then click settings
7. Click “Read code from external file” and browse by clicking the “...” to the `post_run_skim_matrices_25_04_10.py`
8. Finally, click OK

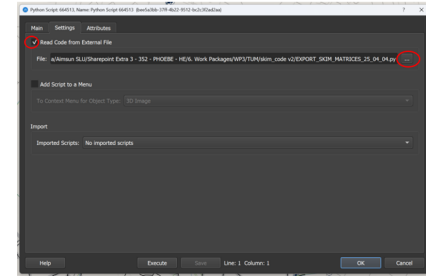


Figure A-35 Reading external code.

9. Check results. Figure A-38 shows the result of a successful script run, folders with the skim matrices in them.

| Name                                   | Status                                                                             | Date modified    |
|----------------------------------------|------------------------------------------------------------------------------------|------------------|
| slurm_topo06705                        |  | 31/03/2023 17:29 |
| slurm_topo06724                        |  | 04/04/2023 10:14 |
| edgemon_24_12_02_AQ04.sang             |  | 03/04/2023 13:09 |
| edgemon_24_12_02_AQ04.sang.ick         |  | 03/04/2023 18:09 |
| edgemon_24_12_02_AQ04.sang.old         |  | 03/04/2023 11:04 |
| edgemon_24_12_02_AQ04.sang.ite         |  | 03/04/2023 12:27 |
| Flowon_Feal Data Set DF_0700_1300.saps |  | 23/04/2024 11:56 |
| Flowon_Feal Data Set DF_1100_1300.saps |  | 23/04/2024 11:56 |
| Flowon_Feal Data Set DF_1300_1900.saps |  | 23/04/2024 11:56 |
| Results_Edgemon_12h.saps               |  | 03/04/2023 15:27 |

Figure A-36 Checking results.

## Set the Script as Post Run

1. Now you have the script in Aimsun.
2. Double click on the experiments you need to export the skin matrices
3. Then select the script in the post-run

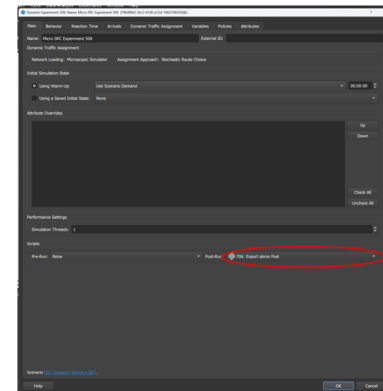
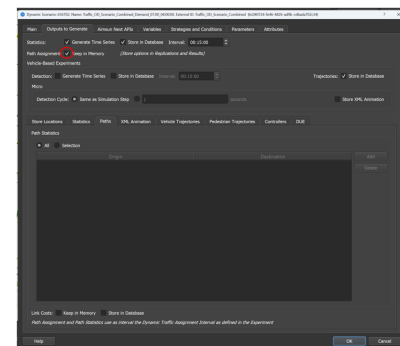


Figure A-37 Selecting the experiments

4. Make sure that the Path assignment is kept in memory; otherwise, it cannot export the skim matrices.



*Figure A-38 Keeping Path Assignment in Memory*

## Get Aimsun Shortest Path Between OD Pairs

This is done using the GUI

1. Open your network and go to "Data Analysis" -> "Shortest Path Calculator..."

2. Select the “Skim Matrices” option and your relevant centroid configuration
3. Click on “Calculate.”

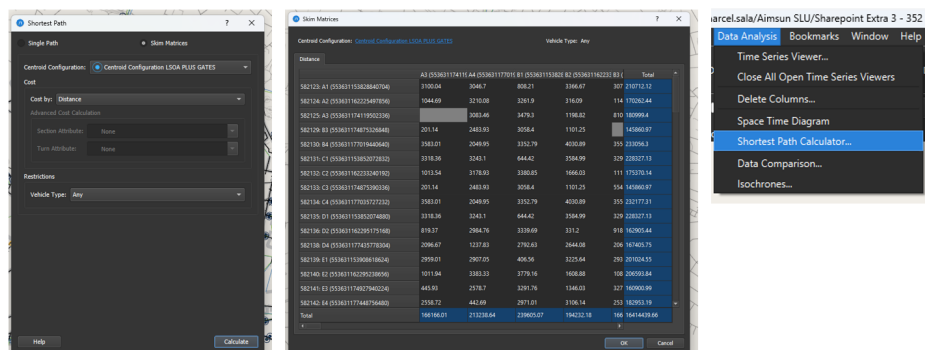


Figure A-39 Commands to calculate the shortest path

4. Copy all the values by clicking on the table's top left and clicking copy.
5. Paste it into a text editor (you can use Excel as well) and save it as a CSV file. Note that if you use “,” as the decimal separator, this needs to be changed to “.”

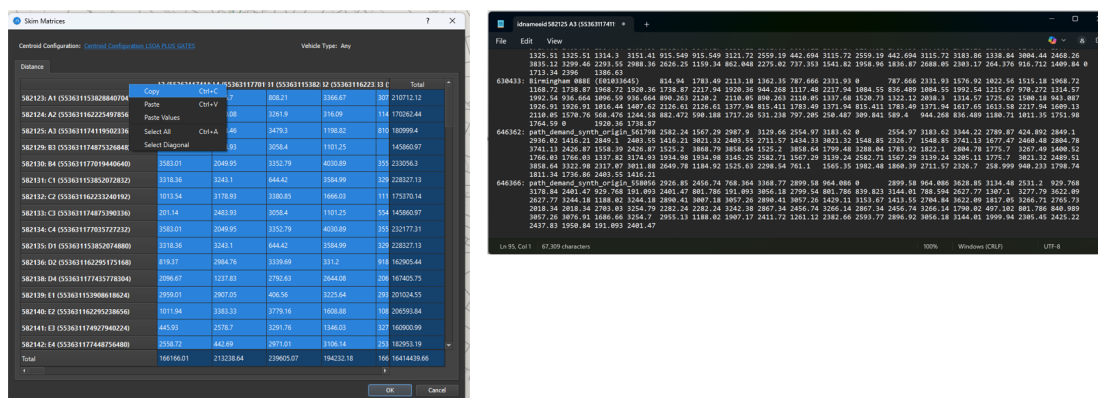


Figure A-40 Exporting the shortest path

### Alternative Approach: Generate Skim Matrix From the Database



- It is possible to generate something very similar to a skim matrix from the database with some caveats:
  - It is not able to have cost information
  - Only considers trips that have been completed, so any en-route vehicles are lost. In small, free-flowing networks, this is not a big deal; in large or congested networks, it has a significant impact.
  - Centroid information needs to be stored.

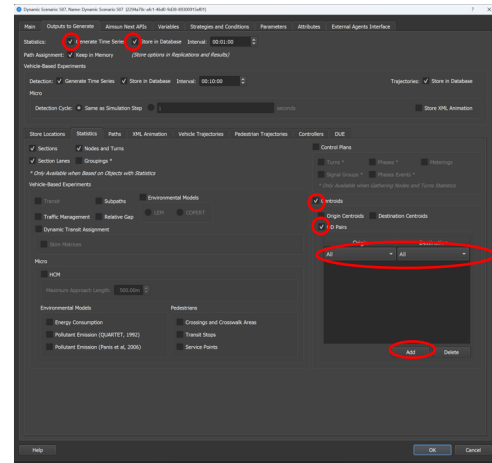


Figure A-41 Alternative approach to generate skim matrices.

- Open a local copy of the file `skim_from_db_XX_XX_XX.py` (the most recent one)
- Place the location into the Python file of the SQLite location, the replications you want to analyse in a list, and set if you want to process vehicles, pedestrians, or both.
- If you run the script in the same folder as the SQLite database, a folder like "DB\_skim\_mat\_rep656724" will appear with all the skim matrices inside.
- The following needs to be checked. This stores OD pair information, in this case: number of trips, distance travelled, and travel time
- As usual, all OD pairs need to be selected, and if they are not, click to add.
- Result should be something like this:
- The particular names of the files and vehicle types will change according to the simulation network

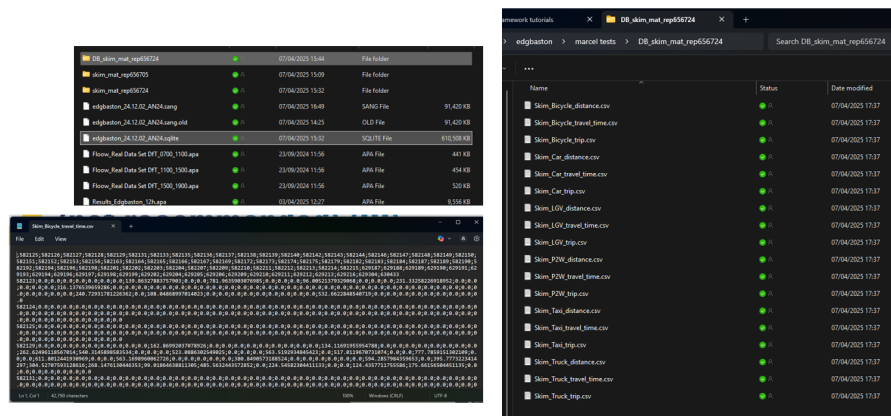


Figure A-42 Example of shortest path extraction

### Batch Run Simulations

- A script is provided to batch run simulations
- It requires the IDs of the replications to be run. The path for the console (Aimsun Next without user interface) is in the same folder as the Aimsun Next executable with GUI.

3. The path to the Aimsun network file (\*.ang)
4. The code will print some information while running and store log files in a dedicated subfolder in the exact location as the Aimsun network file.

#### Import Segmented OD Matrices

1. Add the script "import\_segmented\_matrices\_25\_04\_15.py" or a more recent version to Aimsun Next. How to add external Python code has been shown before.
2. The script is currently targeted to demand that is aggregated per Age and gender, but disaggregated in terms of mode and time, as shown in the list on the right.
3. Update the input section of the script, at the beginning, with your parameters. Documentation on what is expected is on the script itself. You need to add four variables:
  - segmented\_matrices\_2\_import
  - SUBNETWORK\_ID
  - CENTROID\_ID
  - VEH\_MAP
4. Execute the script, and the matrices in the given folders should be imported. A demand object spanning the duration of all the matrices should be ready to use. In this case, it is the "Baseline test import" which can now be selected as a demand on the scenario.
5. Note 1: You might want to test this first on a copy of the Aimsun network
6. Note 2: You might want to duplicate the scenario, so you have a baseline with the original demand and one with the segmented demand.

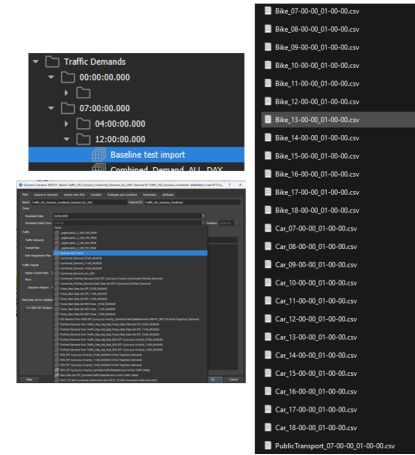


Figure A-43 Importing segmented matrices.

## A.8 Assumptions – Mode shift and Induced Demand

### Athens

Table A-2 Variables Assumptions for the Athens mode shift model

| Variable (predictor mode choice) | Values                                                               |
|----------------------------------|----------------------------------------------------------------------|
| Travel cost car (Running)        | 0.26 €/KM                                                            |
| Parking (2 hr) for a car         | 4 €                                                                  |
| Travel cost of public transport  | 1.2 € flat                                                           |
| Travel cost of a motorcycle      | 0.15 €/KM                                                            |
| Parking (2 hr) for motorcycle    | 0.25                                                                 |
| Travel cost shared micromobility | Unlock 1€ + 0.25€/min                                                |
| AWET Car                         | Access 3 min + 5 min Egress                                          |
| AWET public transport            | Access 5 min + Wait 5 min (Trips > 2 km), 0 otherwise + 5 min Egress |
| AWET motorcycle                  | Access 1 min + 2 min Egress                                          |
| AWET shared micromobility        | Access 3 min + Egress 2 min                                          |



### Valencia

Table A-3 Variables Assumptions for the Valencia mode shift model

| Variable (predictor mode choice)      | Values                                                               |
|---------------------------------------|----------------------------------------------------------------------|
| Travel cost car (Running)             | 0.26 €/KM,                                                           |
| Parking (2 hr) for car                | 5 €                                                                  |
| Travel cost of public transport       | 1.5 € (Trips <= 2KM), 2.80€ Otherwise                                |
| Travel cost of private micro mobility | 0.05 €/KM                                                            |
| Travel cost shared micro-mobility     | Free (First 30 min), 1.04€ (30 min to 60 min), 3.99€ otherwise       |
| AWET Car                              | Access 3 min + 5 min Egress                                          |
| AWET public transport                 | Access 5 min + Wait 5 min (Trips > 2 km), 0 otherwise + 5 min Egress |
| AWET shared micromobility             | Access 3 min + 2 min Egress                                          |
| AWET private micromobility            | Access 1 min + Egress 2 min                                          |
| Average Walking speed                 | 4.4 Kmph                                                             |

### West Midlands

Table A-4 Variables Assumptions for the Valencia mode shift model

| Variable (predictor mode choice)      | Values                                                               |
|---------------------------------------|----------------------------------------------------------------------|
| Travel cost car (Running)             | 0.45 GBP/Mile,                                                       |
| Parking (2 hr) for car                | 3.54 GBP                                                             |
| Travel cost of public transport       | 4.8 GBP (Day ticket), 2.4 GBP (Single trip)                          |
| Travel cost of private micro mobility | 0.09 GBP/Mile                                                        |
| Travel cost shared micro-mobility     | Unlock 1.03 GBP + 0.14 GBP/Min                                       |
| AWET Car                              | Access 3 min + 5 min Egress                                          |
| AWET public transport                 | Access 5 min + Wait 5 min (Trips > 2 km), 0 otherwise + 5 min Egress |
| AWET shared micromobility             | Access 3 min + 2 min Egress                                          |
| AWET private micromobility            | Access 1 min + Egress 2 min                                          |
| Average Walking speed                 | 3.125 mph                                                            |

