eMOTIONAL Cities

Mapping the cities through the senses of those who make them

DELIVERABLE 7.7

# Showcase results report and Policy recommendations

## WP7 – Scenario Discovery

28.02.2025

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# Executive Summary

This document is the deliverable "D7.7: Showcase results report and Policy recommendations" that belongs to the "WP7: Scenario Discovery" of the European project "eMOTIONAL Cities: Mapping the cities through the senses of those who make them" (Project Number 945307; Project Acronym eMOTIONAL Cities).

This report relies mainly on activities from T7.5, "Scenario Discovery Library," T7.4, "Metamodeling Library," T7.1, "Methodological Foundations," and T7.2, "Specification of Case Studies with Cost-effectiveness Analysis," within WP7, as well as on the policy recommendations from WP2 that drove WP7 analysis.

# Terminology and Acronyms

| Term | Acronyms |
|---|---|
| **AL** | Active Learning |
| **EI** | Expected improvement |
| **GP** | Gaussian Process |
| **KPI** | Key Performance Indicator |
| **LHS** | Latin Hypercube Sampling |
| **PRIM** | Patient Rule Induction Method |
| **RDM** | Robust Decision Making |
| **SD** | Scenario Discovery |

# 1. Overview

To draw policy insights from the performed research, we focus on (1) translating scientific research into actionable insights from our experiments and associated data analysis and (2) showcasing scenario discovery.

Within the first thread, we first revisited the work activity in WP2 and formulated general policy recommendations in urban planning for better mental health. These general recommendations are described in section 2 of this report and formed the ground for defining the showcasing of scenario discovery. Furthermore, and more importantly, these general policies were complemented by eight policy briefs that form the key direct contributions to policy recommendations from all activities within eMOTIONAL Cities.

Within the second thread, we explore the libraries for scenario discovery previously presented for showcasing its application in a selected policy and case study. The scenario discovery process aims to support the definition of possible urban futures, and its vulnerabilities under uncertainty, making the research findings directly applicable to urban planning and governance decision-making. Moreover, recommendations are supported by metrics and thresholds, leveraging policy action efficiency and making it more tailored to the community. During WP5 and WP6 of the eMOTIONAL Cities project, models were developed to establish relationships between individual emotions and the urban environment, grounded in empirical evidence from various indoor and outdoor experiments. WP7 focused on applying these models to policymaking, particularly in urban design, land use, infrastructure, and transportation.

# 2. General policy recommendations for better mental health

As an outcome of WP2, some general policy recommendations for better mental health are presented in this section, which served as an information base for developing the specific case studies presented later in this document.

## 2.1 Greenspace

Access to nature and greenspace has been associated with better mental health outcomes, including reduced stress, anxiety, depression, and aggression. This is especially critical for those living in dense city areas and/or those who do not have access to personal yard spaces. Some policy recommendations to increase greenspaces could be:

1. Striving to ensure each neighbourhood is within walking distance of a park, greenspace or trail system. Cities should improve walkability and/or public transit connection to existing parks and identify land for green space restoration.
2. Park quality and accessibility are also important, especially for motivating people to visit and stay at the park [1], and to promote social interaction. Some amenities that cities should consider for parks include but are not limited to:

- Walking trails.
- Shaded and quite areas, that work as climate shelter and calming landscapes/spots.
- Areas for gathering and community events that include seating and tables.
- sensory gardens, spaces with fragrant plants, textured pathways, and calming sounds to stimulate the senses and promote relaxation.
- Water features/gardens/aesthetic components.
- Fitness stations/sports facilities.

3. Increase gardens and greenspace on city-owned land. Some examples are:
    - Community gardens
    - urban gardens
    - Native landscapes > lawn
    - Rooftop gardens
    - Vertical green walls
4. Promote on social media and find ways to motivate and inform people about green initiatives and activities. For example, East Lansing has “No Mow May”.
5. Open-air performances, spaces, that attract people to green spaces and to interact with the space
6. Integrate smart and digital amenities, such as free public Wifi and charging stations that invite and promote remote work outdoors in green spaces

## 2.2 Bluespaces

Like greenspace, it is important to maintain blue spaces and make them accessible. These include natural streams, waterfronts, coastal areas, rivers, and lakes, as well as manmade spaces like fountains, canals, and splash pools [2], [3].

1. Guarantee equitable access to bluespaces, and expand accessibility while enhancing the connection with water.
2. Eco-Friendly Floating Walkway Paths allow visitors to experience water immersion safely.
3. Provide visual accessibility and cues to the water, e.g. spots to rest, reflect, and enjoy the water views.
4. Create community gathering spaces, Amphitheaters, or pavilions near the water for cultural events, music, and socializing.
5. Encouraging low-impact, water-based recreation, that captures people's interest in outdoor activities, sports, and active living, e.g. Kayak, Canoe & Paddleboard Launch Points, fishing platforms, etc.

## 2.3 Walkability & Mobility

Safe, connected, convenient walkways and transit systems encourage people to get around actively outdoors without a personal vehicle. Numerous studies have linked exercise and time outdoors to mental and emotional well-being.

Creating street design guidelines that support **high-visibility** environments is ideal, like brightly coloured paint, flashing signs, reflective bollards, or some kind of separating element from the street for bike paths. This increases safety and boosts aesthetic and placemaking, which is also linked to mental well-being. Some other examples are:

- Bike paths should feel safe and allow for maximum visibility of the biker, as in Figure 1.
- Bus stops should also feel safe and inclusive. Bus shelters can include “public art” or include green elements like plant walls or roofs.


**Figure 1. Example of cyclists in well-defined bike paths**

## 2.4 Community & Connectedness

Research has linked feelings of belonging and community connectedness to increased emotional health. Health in older adults is significantly improved by a sense of community [4]. Supporting the development of spaces where people can gather and feel connected to the community is essential. These spaces may include community centres, sports and fitness centres, theatre/museum/art exhibits, and opportunities for volunteer and part-time work opportunities [5]. Some policy recommendations may be:

1. Encourage mixed-land use to increase the proximity of living spaces to spaces where people can interact/shop/play/volunteer in their community.
2. Support public gatherings and event spaces such as community centres, parks, plazas, and open spaces.
3. Use street design guidelines to encourage vibrant streetscapes with seating places (e.g. benches and tables) and interaction through art and games. Additionally, street designs allow adaptability for seasonal events and decoration. An example of a complete street guideline is presented in Figure 2.

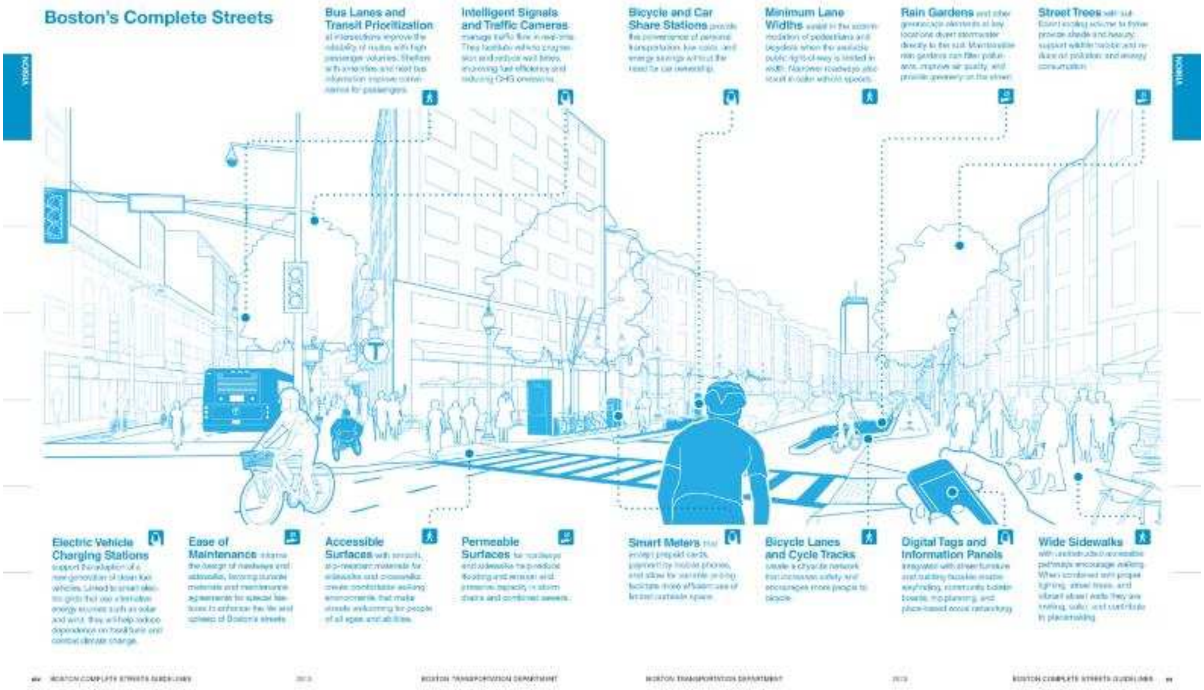



**Figure 2. Example of Boston's complete streets guidelines**

4. The internet is a source of connection and information. Improve access to the internet overall and encourage free Wi-Fi in public spaces such as community centers, public transit, public buildings, libraries, etc.

## 2.5 Noise & Nuisance

Light pollution disrupts the natural circadian rhythm of humans and wildlife, impacting sleep and physical and mental health [6]. Policies that support down-angled lighting and minimise unnecessary lighting at night (especially blue light) can help mitigate these effects.

High noise levels can also disrupt sleep and quiet relaxation; enforcing noise policy and ensuring neighbourhoods are free of overly noisy uses is important to maintaining a peaceful living environment. Additionally, adding trees and other barriers, reducing traffic, and improving building insulation can all help reduce noise. Noise can be managed through zoning and physical design elements such as:

- Planting trees and hedge buffers.
- Placement of water features to drown out traffic and other noise (Or anything else that creates white noise).
- Wall placement between desired quiet spaces and noisy spaces.

Air pollution is linked to worse mental health outcomes [7], [8], [9], like dementia [10]. Cities can work towards reducing their impact through:

- Tree canopy and landscape requirements
- Increased greenspace
- Air quality monitoring
- Controlling industrial pollution
- Encouraging alternative and eco-friendly transit

# 3. Policy Briefs

The eMOTIONAL Cities produced eight policy briefs as a result of the whole research activities. These concise documents communicate research findings and their policy relevance to decision-makers. It includes a clear title, a summary of key points, and an introduction that explains the issue's significance, in an accessible, engaging, and practical form for policymakers and stakeholders. It briefly presents our research findings, case studies, and discussions, followed by a section on policy implications that connect insights to real-world applications. The list of policy briefs is presented below and to avoid repetition, we point the reader to the project website for reading each document: https://emotionalcities-h2020.eu/resources/:

1. Key linkages between urban environments and public health (MSU)
2. Strategies for Accessible and Reusable Data (ByteRoad)
3. Leveraging Spatial Analysis for Improved Urban Health and Well-being (U. Cambridge)
4. Policy recommendations from the results of Neuroscience Experiments (FMUL)
5. Understanding Urban Well-being through Brain Research (StarLab)
6. Policy showcase on scenario discovery for sustainable urban health (DTU)

# 4. Showcasing Scenario Discovery

Scenario Discovery is a more comprehensive exploration of potential solutions under uncertainty. A detailed description of the theoretical background behind it is available in the technical note “Scenario Discovery II” associated with Deliverable 7.6. Within eMOTIONAL Cities, and given that our experiments are limited in sample size (and therefore in representativeness and heterogeneity), urban environment exposure (covering only a select number of urban contexts and cities), and emotion measurement techniques (which are themselves innovative), we showcase here how addressing uncertainty can be handled with Scenario Discovery

We present the methodology, results, and policy implications of a Scenario Discovery study on urban features interventions by assessing possible emotional outcomes from neighbourhood walks. Other case studies proposed in Deliverable 7.1 were built during the project (conceptually for Case Study 3, and in a simulation environment for Case Study 1 - see D7.5) with the associated XLMR framework. Scenario Discovery in Case Study 1 was carried out and presented in D.7.6, aiming to test and validate different algorithms and their computational efficiency under complex simulation.

Figure 3 shows the design overview of the showcasing Case Study at stake. To accomplish our goal, we employed the data collected in **Experiment 2**: **Understanding the neuronal processing of urban space through naturalistic stimuli** of the eMOTIONAL Cities project, where Lisbon-based participants watched first-person videos of the city that were carefully selected to capture different city hotspots. We collected self-reported data on participants' arousal and valence levels while they watched the videos. This data was then used to build a stress model predictor containing individual and environmental features to link the urban spaces with the individual's well-being.

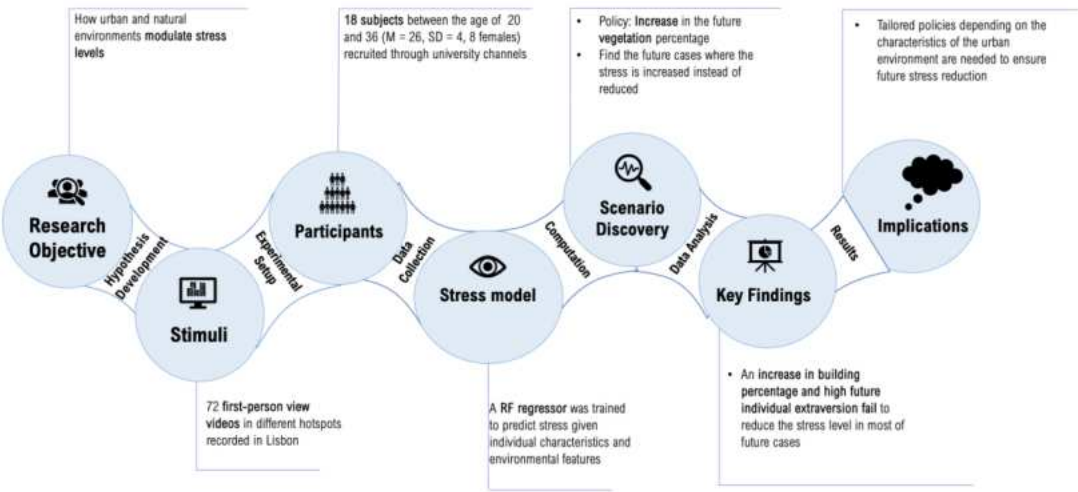



**Figure 3. Design Overview of our Case Study**

To extrapolate our results, this model was then used to evaluate previously selected paths around Copenhagen to understand the urban environment's role in the stress level under different environments. Similarly to the Lisbon case, the Copenhagen paths were selected through the project hotspot spatial analysis and were also the setting for Experiment 4 (see Technical Reports entitled "Methodological report for mapping hotspots in Lisbon" and "in Copenhagen": https://emotionalcities-h2020.eu/resources/).

Following the insights from Section 1 above, increasing the vegetation percentage was the policy chosen to test in Scenario Discovery. As described in the previous section, this has the potential of multiple benefits associated with better mental health.

Then, the Scenario Discover technique explained in Deliverable 7.3, was applied to investigate future cases where our selected policy will fail to meet its goal and the conditions needed to reduce stress levels.

Finally, the key findings for each selected path will be explained, and some general implications will be presented.

## 4.1 Lisbon data collection

As a first step, self-reported evaluation data from Lisbon videos was collected as part of Experiment 2: Understanding the neuronal processing of urban space through naturalistic stimuli of the eMOTIONAL Cities project.

Firstly, a neuro-urbanism workshop was performed in Lisbon. It consisted of a participatory analysis of stakeholders and professionals to comment on a spatial data-driven analysis to define areas of interest (hotspots) and identify a 1km path on each, that could afterwards work as an outdoor laboratory for the neuroscience data collection. Sixteen participants from central and local government, non-profit organisations, academia, and architectural and urban planning companies were invited to comment and draw paths in each hotspot based on their sense and empirical knowledge [11].

In parallel, twenty adult participants were selected through the University of Lisbon and eMOTIONAL Cities social media with no psychiatric or neurological disorders history. Demographic information (age, gender, and education level) was collected, as well as some psychological instruments like the HEXACO Personality Inventory-Revised, a tool used to evaluate the major dimensions of personality, which has been shown to influence the emotional evaluation of architectural space. [11]

First-person videos of the selected paths were recorded with a commercial video camera by the same person who aimed to keep the pace of the walk and the angle of vision constant. The selected participants were seated at a viewing distance of 50-55 cm from a 21.5" inch screen with a 1920x1080 resolution. [11] The experimental procedure started with a brief training session to familiarise the participants with the task. After each video, participants were prompted to respond to two affective questions, as shown in Figure 3, "How did you perceive this video?" with answers from 1 = very unpleasant to 9 = very pleasant, and "How did this video make you feel?" with answers from 1 = very sleepy, to 9 = very alert.

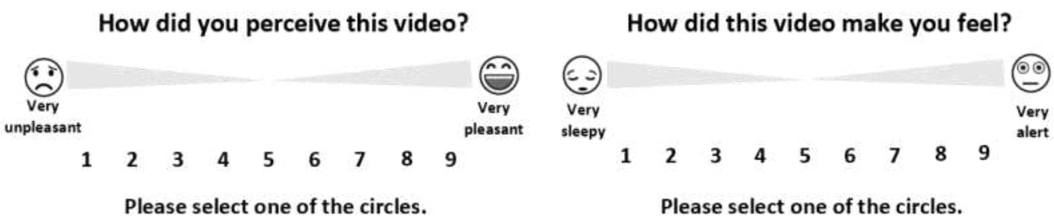



**Figure 4. A modified version of the affective slider [12] for valence and arousal evaluation**

The final dataset consisted of 1256 observations without missing values from the 20 selected participants, 18 subjects between the ages of 20 and 36 years old (M = 26, SD = 4, 8 females) recruited through university channels. Participants watched a total of 72 first-person videos of 20 seconds. Both eye tracking and EGG data were also collected in this experiment, even though they were not used in the following analysis since a more direct relationship with stress levels was desired to construct the stress model presented in the next section.

## 4.2 Stress model

Given the data from the experiment described in the previous section, we trained a Random Forest Regressor to predict the stress given some individual characteristics and environmental features.

We started by building a model to compute the projection of the arousal and valence in a 45º line, as shown in Figure 5, which, in psychological theory, represents the stress level.

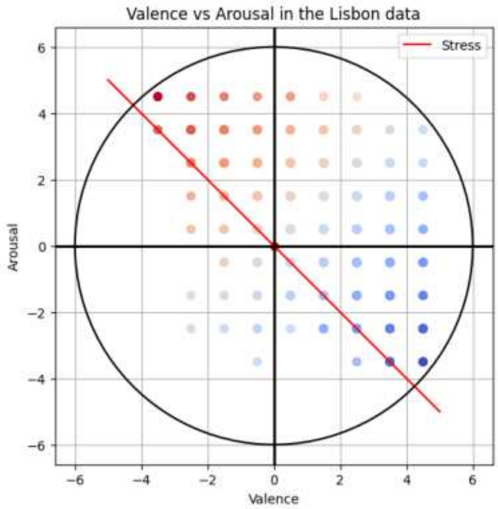



Figure 5. Valence vs Arousal in Lisbon data

Cross-validation was employed to train the **RF Regressor** and tune the model hyperparameters to achieve the best fit. The best Random Forest Regressor consisted of fifty decision tree estimators with a maximum depth of thirty each, a minimum sample for leaves of ten, and two minimum samples to perform a split. Moreover, bootstrap (a sampling technique that involves repeatedly drawing random samples with replacement from a dataset) was employed in the estimation process.

**The coefficient of determination ($R^2$)** is used in the estimation of the model's fit. $R^2$ indicates the proportion of the variance in the dependent variable that is predictable from the independent variables,

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where $y_i$ represents the actual value, $\hat{y}_i$ represents the predicted value, $\underline{y}$ is the mean of the actual values, and $n$ is the number of observations in the test set. Therefore, the closer the $R^2$ is to 1, the greater the variance explained, and the better the model fit.

In our case $R^2 = 0.53$, this indicates that there is still some data variability not explained by the model structure. This could be due to the small sample size of the data and the lack of recorded variables that influence the stress response.

Moreover, to understand how well our proposed model predicts the stress level, we plot the stress prediction for the test data given the valence and arousal coordinates, as shown in Figure 6, where the red points represent higher predicted levels of stress and the blue ones lower. We can see that even though there are some misleading points (some lightly blue points in the upper left corner and some slightly red points in the lower right corner), the model seems to capture the overall stress trend in the test data.

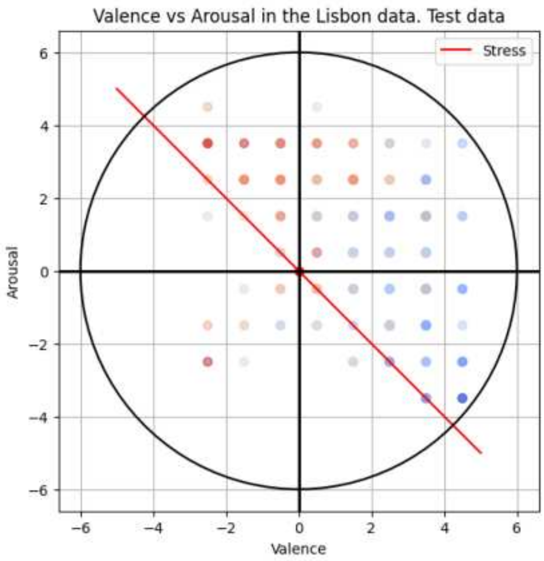



**Figure 6. Stress prediction in the test data**

As an example of a concrete path, we isolated the stress points for all the individuals through a path where the percentage of vegetation is 58%, and the building percentage is 6.6%, and we see in Figure 7 that the self-reported stress is quite low. Similarly, the higher values of predicted stress (more intense red points) are in the higher reported stress levels. It is important to note that, in this case, the variation in stress levels is due to individual characteristics, given that the environmental characteristics remain the same since we are considering the same path.

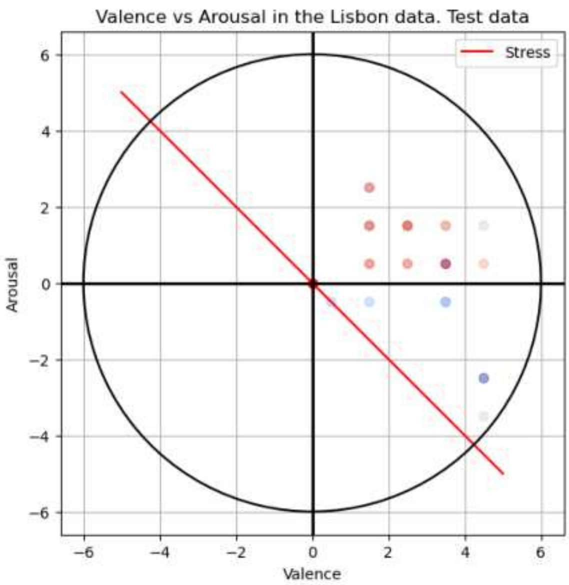



**Figure 7. Stress prediction in a concrete Lisbon path**

Finally, the **SHAP values** were calculated to understand better the role each input variable played in predicting the stress level. SHAP values (Shapley Additive exPlanations) quantify the contribution of each feature to the prediction by distributing the difference between the model's output and a baseline value among the input features. As shown in Figure 8, the higher the percentage of people and buildings, the higher the predicted stress level, as expected given the psychological theory. The same theoretical correspondence happens with the vegetation percentage, extraversion, openness, and general well-being since the higher the value of these features, the lower the predicted stress.

Both openness and extraversion are personality traits described in the *Five-Factor Model of Personality* [13]. The model's traits are Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Personality traits significantly influence how individuals perceive, react to and cope with stress [14]. Personality helps explain why people think, feel and behave differently or similarly in various situations. Evidence supports that personality factors, more so than the environment, play a causal role in how individuals cope and their stress reactions [13]. Greater openness mainly results in beneficial effects on the stress process. Similarly, extroverted individuals generally handle stress better, largely due to their increased sociability. This sociability enables extraverted individuals to seek and receive more social support [13].

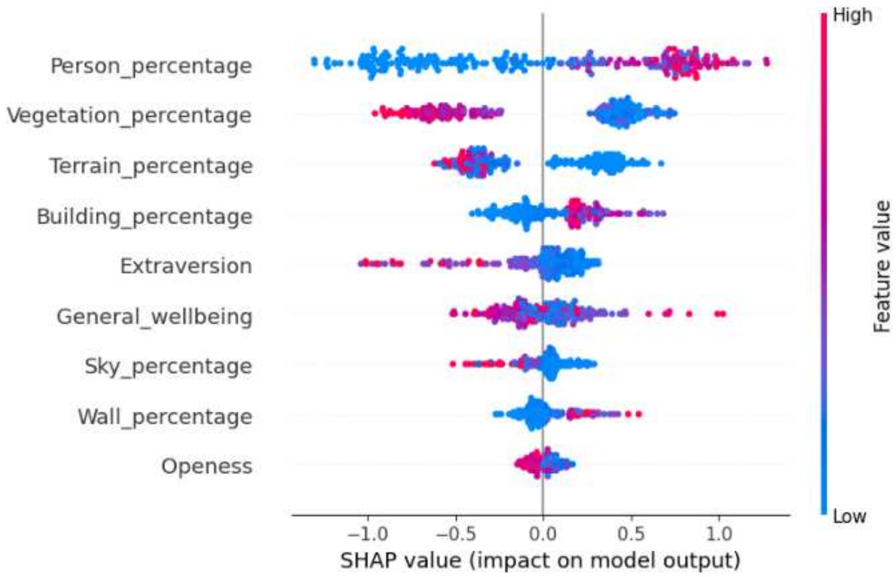



**Figure 8. SHAP values of the stress model**

Regarding the stress predictor model results, to have an order of magnitude of some of the more important features, the mean value through the 72 Lisbon videos of some of the input variables is presented in Table 1. As we can see in the table, the value of the features varies considerably from video to video since they are expected to capture a wide variety of urban sceneries.

| Features | Mean value over all the videos | Minimum mean value over a video | Maximum mean value over a video |
|---|---|---|---|
| Building percentage (%) | 26.47 | 0.0 | 96.07 |
| Vegetation percentage (%) | 33.31 | 0.07 | 95.75 |
| Person percentage (%) | 10.23 | 0.0 | 46.12 |
| Extraversion | 3.12 | 3.02 | 3.14 |

**Table 1. Mean value in Lisbon data of important analysed features**

## 4.3 Copenhagen application

Given the stress level predictor model trained with the Lisbon data, we aim to extrapolate these results and apply them to different paths in Greater Copenhagen to understand better how different urban and individual features affect stress prediction under different future cases. We aim to develop a policy that will reduce stress levels in Copenhagen in various future scenarios.

### 4.3.1 Data collection in Copenhagen

For the urban features, images from Greater Copenhagen were extracted from a 50x50-meter grid via the Mapillary API, given the latitude and longitude, desired image size, number of images to download per coordinate, and the search radius around each coordinate point. The selected number of images to download per coordinate was 250, but if there were not enough images for some coordinates, the script downloaded as many as were present. Hence, the number of images per coordinate fluctuated. Mapillary images are a proxy for the person walks videos collected in Lisbon.

In the next stage, **image segmentation** was applied to the Mapillary images to extract valuable information from the images. This was accomplished with the Mask2Former, a model that segments images into categories such as roads, buildings, vehicles, and pedestrians [15], introduced in the paper 'Masked-attention Mask Transformer for Universal Image Segmentation [16].

After segmenting each image, the presence of each object type was calculated and converted into percentages. The pixels that belong to each object category are counted, and these counts are expressed as a percentage of the total number of pixels in the image [17], [18]. Once individual images had been processed, the features were averaged to compute the mean percentage for each object type across all images within the same coordinate. This averaging step shows the most prevalent features in the images from a specific geographic location, providing an average depiction of the scenery around a given coordinate. [19] In Figure 9, we can see an example of a raw image and its annotated image.

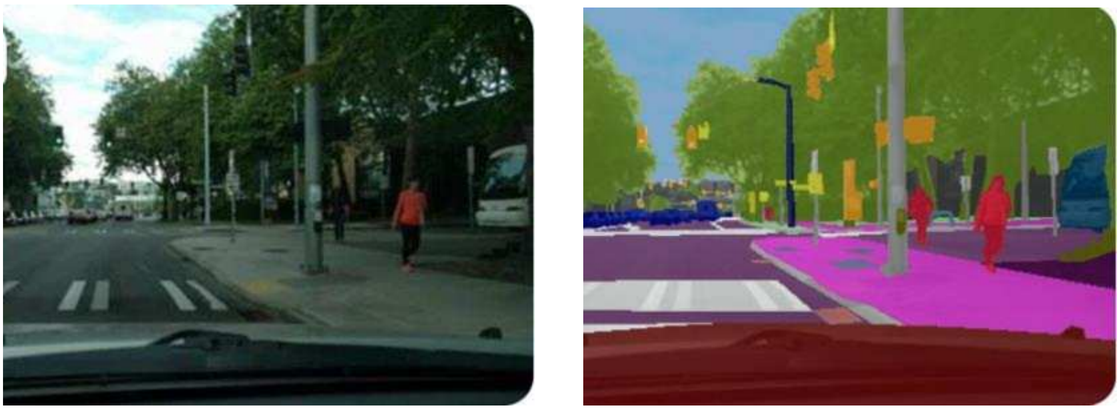


Figure 9. Example of raw image and annotated image [17]

The classes used for the segmentation for the Mapillary Vistas Class are listed below in Table 2 and will be the final features given in percentages.
For our study, different paths throughout the city of Copenhagen were selected. Each path represents a different city area and contains different environmental features. This variability allows us to explore how the policies develop in different environments.

This path selection was an outcome of the eMOTIONAL Cities Spatial Analysis activities in WP4 and is documented in the Technical Report, “Methodological report for mapping hotspots in Copenhagen” (https://emotionalcities-h2020.eu/resources/) [20].

| Class IDs | Description |
|---|---|
| *13, 24, 41* | *Road, Lane Marking - General, Manhole* |
| *2, 15* | *Sidewalk, Curb* |
| *17* | *Building* |
| *6* | *Wall* |
| *3* | *Fence* |
| *45, 47* | *Pole, Utility Pole* |
| *48* | *Traffic Light* |
| *5* | *Traffic Sign (Front)* |
| *30* | *Vegetation* |
| *29* | *Terrain* |
| *27* | *Sky* |
| *19* | *Person* |
| *20, 21, 22* | *Bicyclist, Motorcyclist, Other Rider* |
| *55, 1* | *Car* |
| *61, 53* | *Truck* |
| *54* | *Bus* |
| *58* | *On Rails* |
| *57* | *Motorcycle* |
| *52* | *Bicycle* |

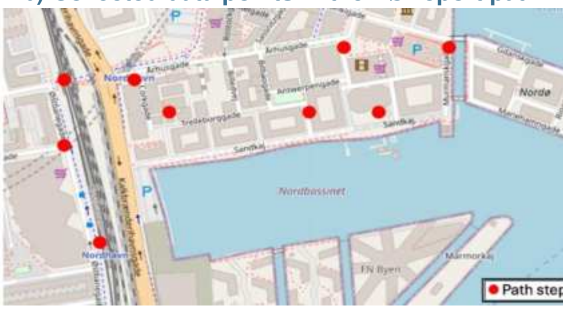
Table 2. Mapping of class IDs to descriptive labels for semantic segmentation [18].

In Figure 11, we plot the selected paths with the data points where the feature percentages from the Mapillary images were extracted to analyse each path.


a) Collected data points in the Nørrebro path


b) Collected data points in the Nørreport path

c) Collected data points in the Hellerup path



d) Collected data points in the Nordhavn path

**Figure 11. Collected data points in the Greater Copenhagen area**

As shown in Figure 12, these points were selected based on the paths used for Experiment 4: Outdoor neuroscience experiment: “eMOTIONAL cities walker” conducted in Copenhagen.

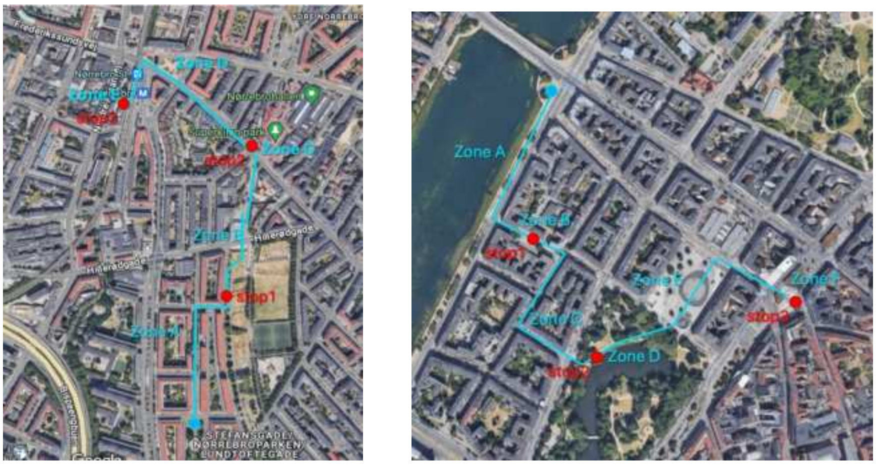


**Figure 12. Copenhagen path selection for the walk experiment**

After extracting the images and averaging the percentage among all the points in each path, Table 3 shows the percentage for the most important features for the Scenario Discovery analysis.

| Features | **Nørrebro** | **Nørreport** | **Hellerup** | **Nordhavn** |
|---|---|---|---|---|
| Vegetation percentage (%) | 10.22 | 16.57 | 12.6 | 6.25 |
| Building percentage (%) | 24.7 | 22 | 25 | 26.5 |
| Person percentage (%) | 0.82 | 0.46 | 0.24 | 0.26 |

**Table 3. Percentage of environmental features for each considered path**

While Nørreport is the path with more vegetation percentage (16,6%) due to the proximity to the lakes and the Ørstedsparken garden, Nordhavn has less vegetation (6.25%) since it is a newly urbanised area, and it is close to the train rails and blue area as shown in Figure 13.

**Figure 13. Google Images taken from the Nørreport (Zone D) and Norhavn (Zone E) paths**

It is worth noticing that the percentage of people is very low compared with the data from Lisbon (Table 1) since Mapillary images purposedly minimize the number of people on them. However, this doesn't mean these areas aren't very populated. To correct this bias, 10% more of the person percentage has been imposed before normalisation with the other features in all Copenhagen's pictures.

### 4.3.2 Policy consideration

Given the information present in our stress predictor model and the characteristics of the Copenhagen paths, we studied which kind of policy could be applied in this case study to increase well-being and reduce stress.

We opt for **ensuring better access to green spaces** and nature since it has been associated with better mental health outcomes, as shown in Section 1, including reduced stress, anxiety, depression, and aggression. Moreover, high noise levels can arise in the city centre, disrupting sleep and quiet relaxation, and studies have shown that adding trees reduces noise levels. Finally, air pollution is also linked to worse mental health outcomes, and increased greenery can work towards reducing their impact [21]. Other dimensions of interest in this case study are blue spaces from the lakes and the canals around the city, and walkability and mobility, especially by bike, since Copenhagen is well known for its high bike use.

### 4.3.3 Scenario Discovery Framework

The first step to applying Scenario Discovery efficiently is to define the problem based on the RAND's **XLRM framework**, which normally defines the limits and scope of Scenario Discovery.

In the XLRM framework, **X** stands for **Exogenous uncertainties (X)**, which are all the variables we have no control over; however, they play an essential part in the possible outcomes of our actions. **Policy levers (L)** are the actions policymakers can apply to modify the current environment. **The Relationships (R)** are potential ways the future could evolve based on the policymakers' choices of levers and the manifestation of the uncertainties. Typically, the relationships are equivalent to the run of a simulation model. Finally, **Measures (M)** are the performance standards that policymakers and other interested stakeholders use to rank the desirability of various scenarios [22].
Table 4 shows the **XLRM framework** when applied to this case study,

| | |
|---|---|
| **Uncertainties (X)**<br>Individual characteristics: extraversion<br>Environmental features: building percentage and person percentage | **Policy levers (L)**<br>Increase the vegetation percentage in each step of the path |
| **Relationships (R)**<br>The RF stress model defined above | **Measures** (**M**)<br>A vulnerable future case is defined as a scenario where the stress is not reduced but increased after the policy application |

**Table 4. XLRM Framework for our Case Study**

#### 4.3.3.1 Analysis of the uncertainties

We select three uncertainty measurements to explore in our Scenario Discovery Framework. Two of them are the environmental features that impact the stress predictor model most: **building percentage** and **person percentage.** We chose them because of their high impact on predicting the stress response. Moreover, building and person percentages are increasing nowadays in all cities and are expected to increase in the future. So, high variability of these features is expected. We select a variability range from 50% of its baseline value to 150% of it. However, this range will be later reduced, given the normalisation procedure employed to ensure that the sum of all the percentages present at each point in the path doesn't sum more than 100%.

The last uncertainty variable explored is **extraversion**, a personality trait described in the *Five-Factor Model of Personality* [13]. We chose extraversion because it was the individual characteristic that most impacted the stress predictor model, and we consider it helpful to have an uncertainty variable at the individual's level to see its impact on the predicted results. The mean value for this personality trait is 3.12 in the Lisbon data, the minimum value is 2.41, and the maximum is 5. Given that there is no information about personality traits in the Copenhagen data, the average value in Lisbon is selected for the baseline scenario, and a range that goes from 80% to 140% of its value is selected for the uncertainty exploration.

| Uncertainty | Minimum value | Maximum value |
|---|---|---|
| Building percentage | 50% of its value | 150% of its value |
| Person percentage | 50% of its value | 150% of its value |
| Extraversion | 80% of 3,12 = 2,5 | 140% of 3,12 = 4,37 |

**Table 5. Range of uncertainties employed for our Case Study**

### 4.3.4 Results

#### 4.3.4.1 Percentage of vegetation needed

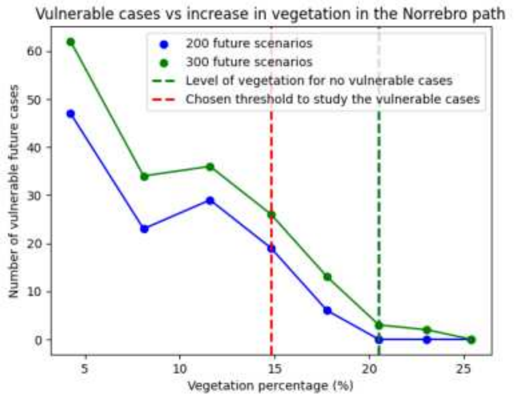
Firstly, to study the percentage of vegetation needed to accomplish our policy of reducing stress levels, 200 and 300 future LHS scenarios were run for different values of vegetation.

Figure 14 shows the number of vulnerable cases for each combination of vegetation percentage and the number of future scenarios for each selected path. Two insights can be taken from this figure. The first one is that jumping to 300 scenarios doesn't affect the vegetation percentage threshold for which the number of vulnerable cases is zero or almost zero. Therefore, there is no extra benefit in performing 300 model runs, and we will continue our analysis with 200 LHS future cases. This comparison could only be performed because the model estimation time is short. Performing so many model runs with a more complex and time-consuming model would have been unfeasible and therefore we would need to resort to the active learning metamodeling approach proposed in D7.6. The second insight we can take from Figure 14 is that the percentage of vegetation needed for not having vulnerable future cases depends on the features of each path. Indeed, around 15% of vegetation is needed in Norrrebro and Nørreport, but only 7% is needed in Hellerup, and up to 22% is needed in Nordhvan. Therefore, more tailored policies could be applied by policymakers.

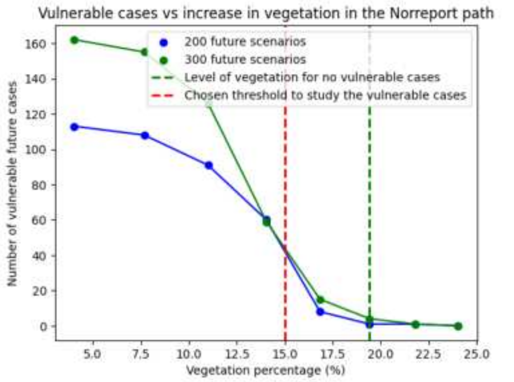
#### *4.3.4.2 Scenario Discovery results for each path*

For each of the selected paths, Scenario Discovery is performed with the previously selected vegetation threshold to study the location of the vulnerable cases, i.e. the futures that experience an increase instead of a reduction of the stress levels, on average for all the points in each path, when comparing with the baseline case (no policy applied).

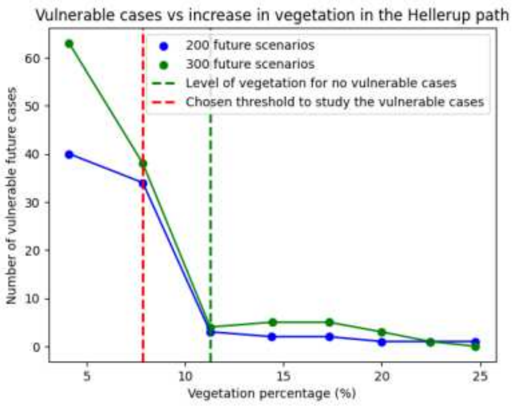
The location of the vulnerable cases gives policymakers and stakeholders a better understanding of the conditions under which the proposed policy won't perform as expected, and it can be useful for monitoring certain future uncertainties to be prepared for when the proposed policy will not serve its purpose and need to be replaced.



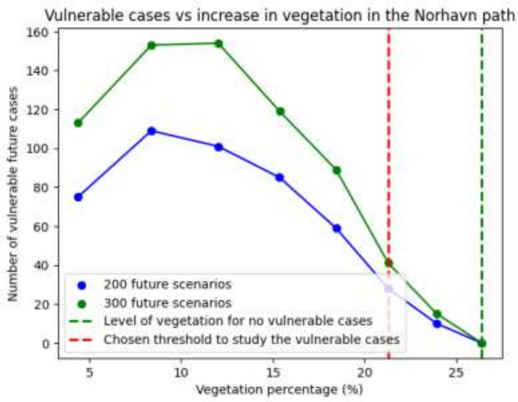

**a) Percentage of vegetation in the Nørrebro path**




**b) Percentage of vegetation in the Nørreport path**




**c) Percentage of vegetation in the Hellerup path**




**d) Percentage of vegetation in the Norhavn path**

**Figure 14. Percentage of vegetation needed for each of the paths**

### Nørrebro path

After normalisation and scenario generation, the average vegetation increase in Nørrebro is 14.81%; with this percentage, the number of vulnerable cases is 19.

Figure 15 shows the decrease of stress compared to the baseline case, average in the points in the Nørrebro path, for the 200 considered future scenarios; on the right picture, the average stress is computed with and without applying the policy for the same 200 LHS point. As we mentioned, most cases experience a stress reduction for the selected percentage of greenery, with the maximum decrease around 0,5.

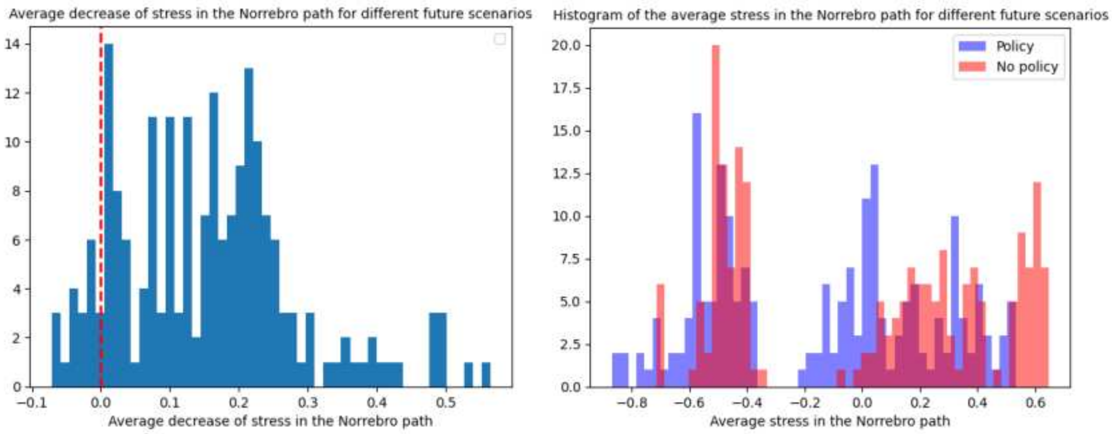



**Figure 15. Decrease in stress in the Nørrebro path for different future scenarios and stress levels before and after applying the green policy**

The PRIM algorithm was employed to highlight the location of the vulnerable cases. More details about this algorithm can be found in Deliverable 7.5 [22]. In a few words, PRIM tries to find regions in the space where the mean is higher (vulnerable points count as one while no vulnerable points count as zero), while balancing coverage (the percentage of the total vulnerable points that are taken inside the box) vs density (the number of vulnerable points taken concerning the total points inside the box).

Figure 16 shows the PRIM box where the most vulnerable cases are concentrated (coverage = 89,5%), when the building percentage goes above 17,3% and the extraversion is more than 3,80%.

Even though we have mentioned before that high extraversion is a protective factor for stress, the reduction of stress concerning the baseline case is lower compared to cases when citizens are less extroverted, and it is paired with higher levels of building percentage. The higher the building percentage, the less space there is for the vegetation levels to increase, which increases the predicted stress. Moreover, given the stress predictor model, high building percentages are correlated with higher stress levels.

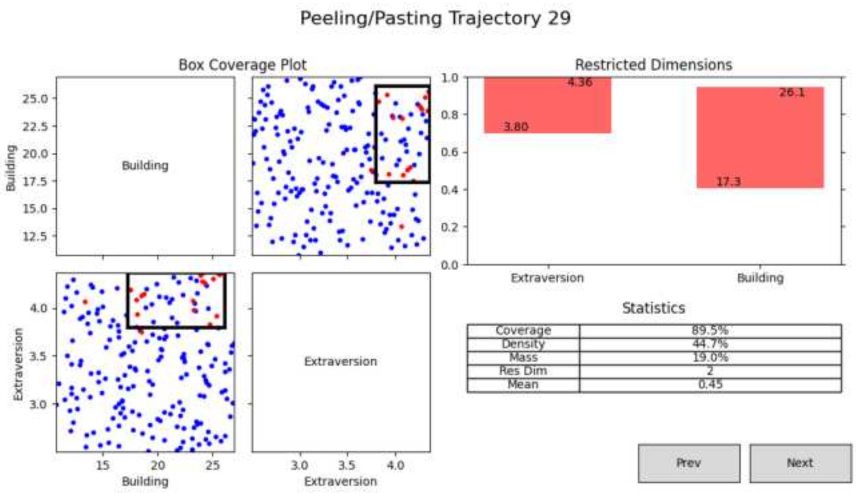



**Figure 16. PRIM box found for the vulnerable future cases in the Nørrebro path**

## Nørreport path

After normalisation and scenario generation, the average vegetation increase in Nørreport is 15.18 %; with this percentage, the number of vulnerable cases is 29.

Figure 17 shows the decrease of stress compared to the baseline case average in the points in the Nørreport path for the 200 considered future scenarios; on the right picture, the average stress is computed with and without applying the policy for the same 200 LHS points. As we mentioned, most cases experience a stress reduction for the selected percentage of greenery, with the maximum decrease around 0,5.

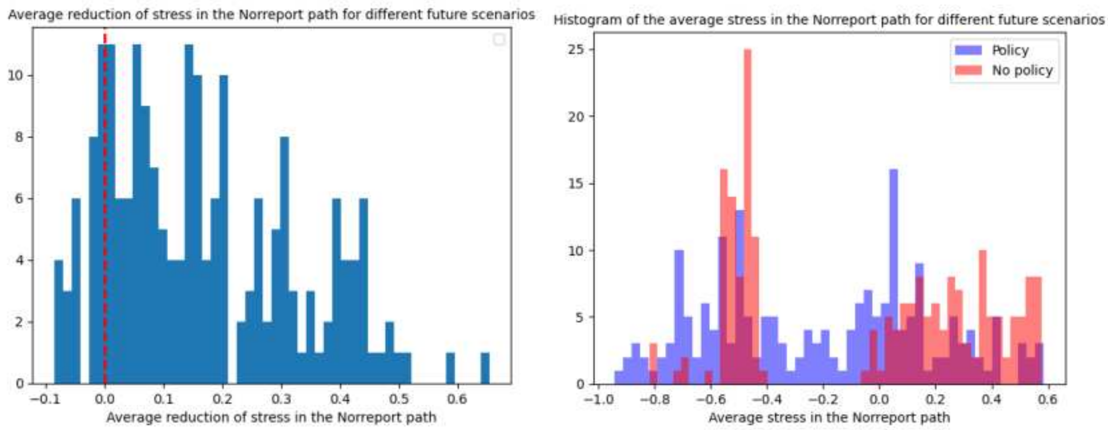



**Figure 17. Decrease in stress in the Nørreport path for different future scenarios and stress levels before and after applying the green policy**

Figure 18 shows the found PRIM box with the vulnerable cases in the Nørreport path, where an increase in building percentage also implies an increase in the vulnerable cases, paired with values of people percentage above 7%. However, unlike in the other paths, extraversion does not seem to be an impactful feature in pointing out where the vulnerable cases are located.

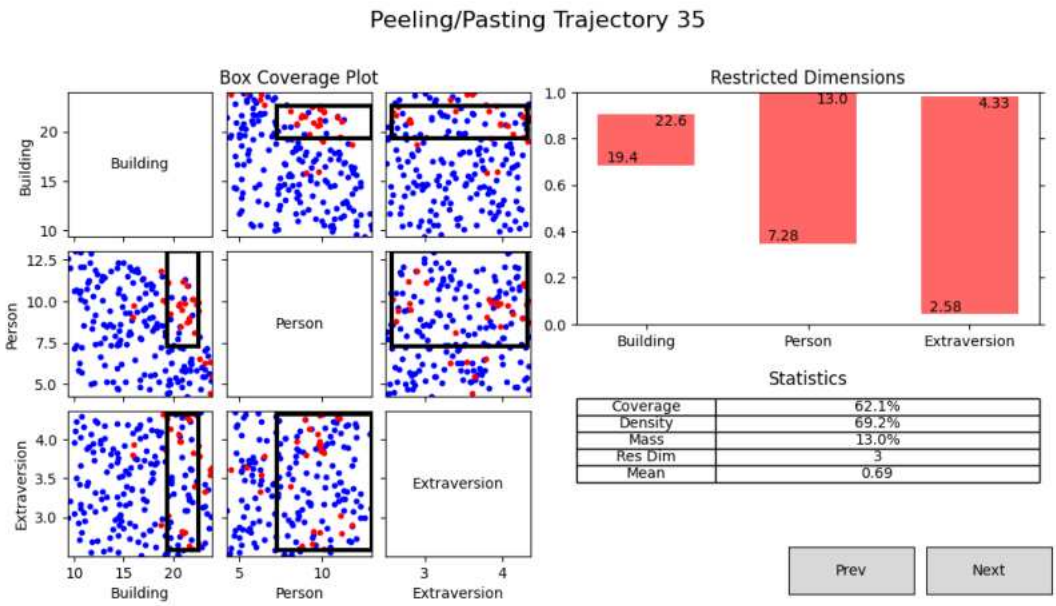



**Figure 18. PRIM box found for the vulnerable future cases in the Nørreport path**

### Hellerup path

After normalisation and scenario generation, the average increase of vegetation in Hellerup is 7.86% and with this percentage, the number of vulnerable cases is 34.

Figure 19 shows the decrease of stress compared to the baseline case average in the points in the Hellerup path for the 200 considered future scenarios; on the right picture, the average stress is computed with and without applying the policy for the same 200 LHS point. As we mentioned, most cases experience a stress reduction for the selected percentage of greenery, with the maximum decrease around 0,4.

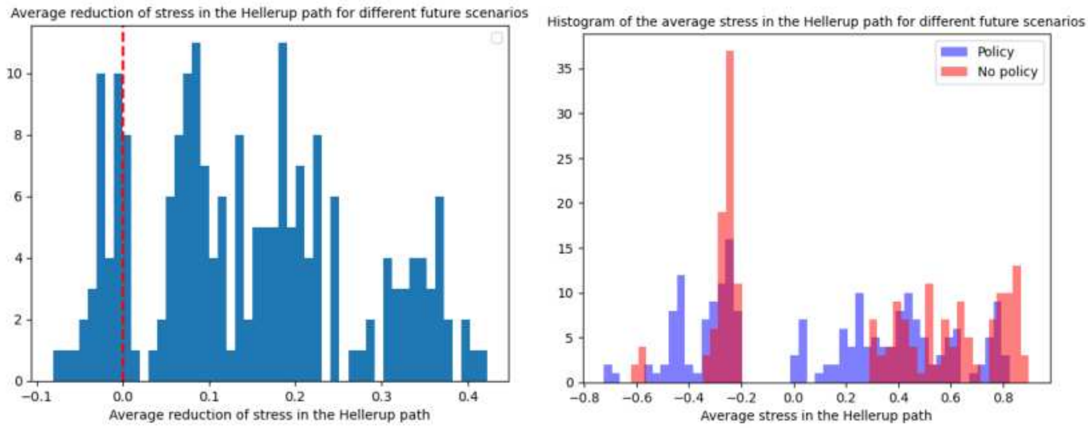



**Figure 19. Decrease in stress in the Hellerup path for different future scenarios and stress levels before and after applying the green policy**

Figure 20 shows the resulting PRIM box with the vulnerable cases in the Hellerup path, where an increase in people and extraversion seem to be the main causes of the prevalence of vulnerable cases. The building percentage is less relevant in predicting the location of the vulnerable cases since its range is wider.

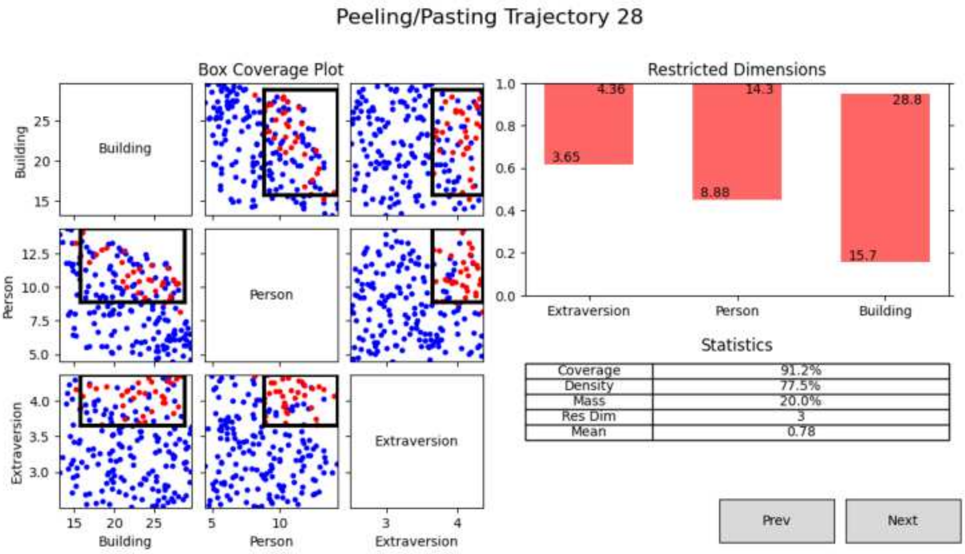



**Figure 20. PRIM box found for the vulnerable future cases in the Hellerup path**

### Nordhavn path

After normalisation and scenario generation, the average increase of vegetation in Nordhavn is 28% and with this percentage, the number of vulnerable cases is 28.

Figure 21 shows the decrease of stress compared to the baseline case average in the points in the Nordhavn path for the 200 considered future scenarios; on the right picture, the average stress is computed with and without applying the policy for the same 200 LHS point. As we mentioned, most cases experience a stress reduction for the selected percentage of greenery, with the maximum decrease around 0,7.

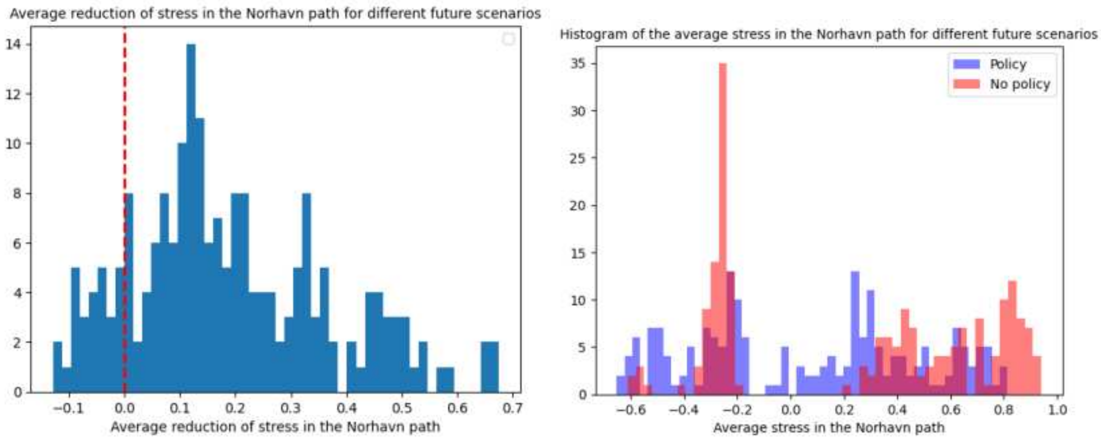



**Figure 21. Decrease in stress in the Nordhavn path for different future scenarios and stress levels before and after applying the green policy**

Figure 22 shows the final PRIM box with the vulnerable cases where we can see that, as in the Nørrebro case, as the percentage of buildings and extraversion increases, the more probable is to find a vulnerable scenario. Even though the person percentage seems to play some role in increasing the vulnerable cases, the correlation is low since its range is quite wide.

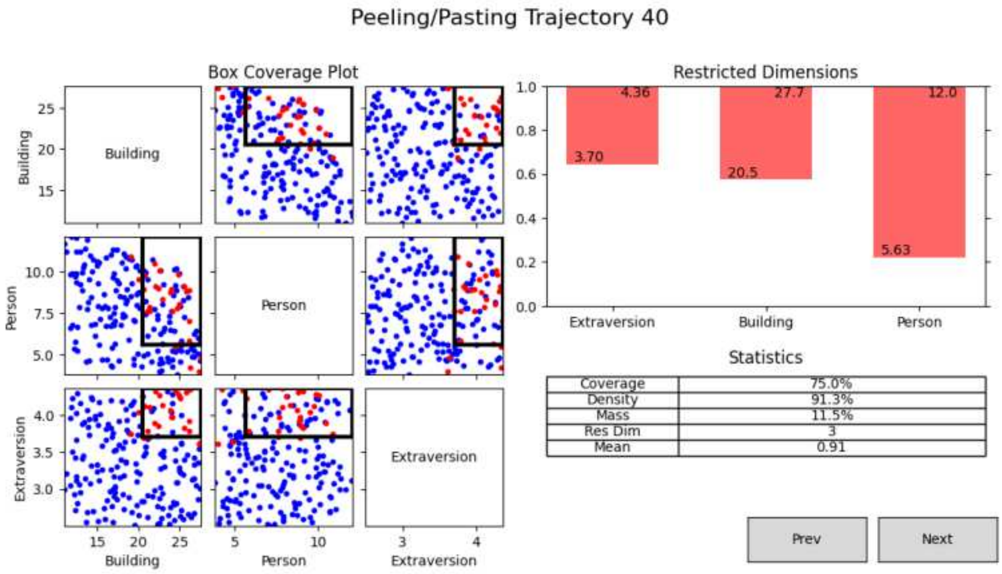



**Figure 22. PRIM box found for the vulnerable future cases in the Nordhvan path**

In conclusion, all the paths have a reduction in the stress levels for most of the cases given the selected levels of vegetation. In general, high building percentage and high future extraversion correlate the most with the location of the vulnerable cases.

### *4.3.4.3 Active learning sampling strategies*

In this last section of the results, PRIM is combined with Active Learning to reduce the number of future scenarios needed to arrive at a similar conclusion.

The Nørrebro path was selected for this small experiment, and 100 LHS initial sampled points were run with the stress model. After that, a Gaussian Process regressor was fit to the data to learn the distribution of the vulnerable points in the uncertainty space.

For each iteration, PRIM was performed, and a point within the found box was sampled and added to the estimation of the GP. More details about this sampling process can be found in Deliverable 7.5 [23].

In total, 50 extra points were sampled, which led to 150 points, 50 less than in the previous section, reducing the running time and resources. In Figure 10, the distribution of true, picked and posterior are plotted together to estimate how well the two distributions of points match. The posterior distribution results from including the information of the picked points in the GP in the same 200 LHS points of the true distribution. Figure 23 shows how these two distributions overlap, meaning that the posterior trained in 150 can capture the overall structure of the 200 LHS computed points, thus saving at least 50 runs

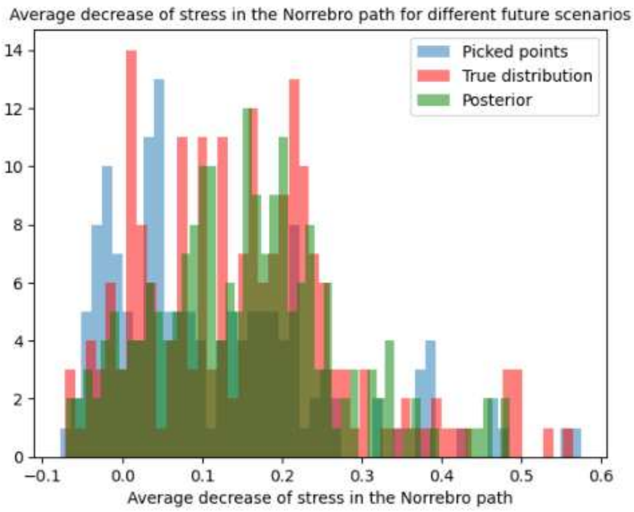



**Figure 23. Distribution of the reduction of stress in Nørrebro for the picked points, the true distribution and the posterior distribution for PRIM-AL sampling strategy**

In Figure 24, we can also see how the correction between the posterior and the true values of the 200 LHS points is quite similar, in concrete 0.887 with an accuracy of 192/200 of well-predicted vulnerable future cases.

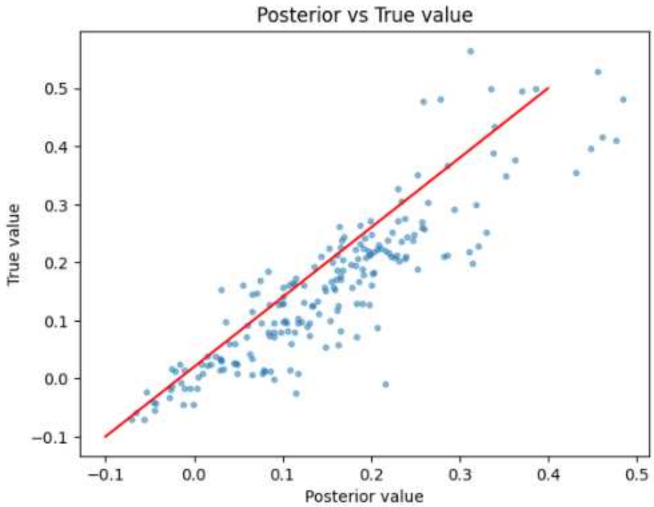



**Figure 24. Correlation between the true value and the posterior distribution prediction for PRIM-AL sampling strategy**

Finally, PRIM-AL borders, a similar sampling strategy, was performed in the same manner as PRIM-AL: 100 LHS sampled points were selected at the beginning, and 50 iterations of the sampling algorithm were performed to select 50 extra points. The only difference between the two sampling approaches is that in PRIM-AL borders, the points are sampled exclusively from the borders of the PRIM box at each iteration.

The comparison with the true distribution of points can be seen in Figure 25. The correlation between the posterior and the true sampled points is 0.894, and the accuracy is 188/200 for well-predicted vulnerable/no vulnerable scenarios.

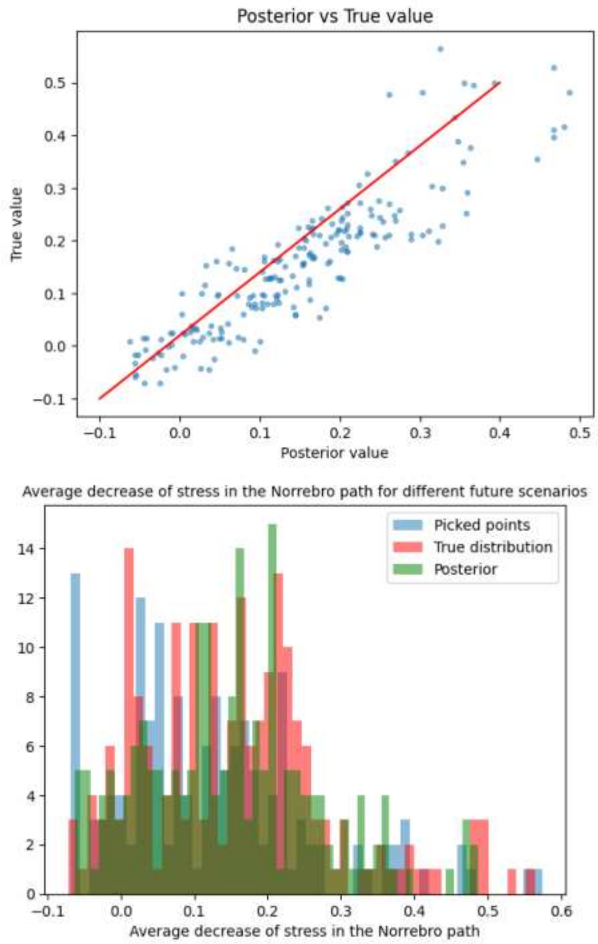



**Figure 25. Distribution of the posterior, true and picked points and correlation between the true and predicted posterior points for PRIM-AL borders sampling strategy**

### 4.3.5 Conclusions

The eMOTIONAL Cities project has provided valuable policy insights by translating scientific findings into actionable recommendations and showcasing scenario discovery methods. First, we revisited the work in WP2 to develop general urban planning policies aimed at improving mental health, which are detailed in Section 2. In this activity, evidence that the built environment significantly impacts the quality of life, independence, and safety of individuals with mild cognitive disorders or dementia was clear. Prioritizing user-centric design tailored to their needs can enhance well-being and social participation. Urban planners and architects are increasingly integrating neuroscience insights to create environments that promote emotional well-being, focusing on walkability, access to green spaces, safe materials, and social connectivity. Understanding how the brain and emotions interact with the built environment allows for urban development that aligns with human neurological and emotional needs, fostering more inclusive and supportive cities.

These broad recommendations along with the work across the different WPs laid the foundation for the scenario discovery approach and were further refined into eight policy briefs, representing the key direct contributions of the eMOTIONAL Cities project to policy formulation.

We demonstrated the scenario discovery process by applying relevant algorithms to a selected policy and case study, highlighting its potential to define urban futures and assess vulnerabilities under uncertainty. This approach enhances urban planning and governance by providing metrics and thresholds that improve policy action efficiency and tailor interventions to community needs.

The case study demonstrated the efficacy of Scenario Discovery in policy-making for urban health by exploring stress levels in different urban environments

- **Effectiveness of Green Policies**: We could infer that increased vegetation cover led to a general reduction in stress levels across all selected paths. However, the required percentage of vegetation to achieve stress reduction varies per location. For instance, Nordhavn required a significantly higher increase (28%) than Hellerup (7.86%).
- **Limitations of Vegetation-Based Policies**: In high-density urban environments, increasing vegetation alone is not always sufficient to mitigate stress, particularly in scenarios, such as the cases of: High building density (e.g., Nørreport, Nørrebro);
- **High presence of people** (e.g., Hellerup, Nørreport); High extraversion levels among individuals, where stress responses to urban environments are more varied.
- **Scenario Discovery for Policy Resilience**: the study identified vulnerable cases where greenery policies fail, guiding policymakers to adjust interventions proactively. For instance, in Nørrebro and Nordhavn, the combination of high building density and extraversion traits indicated a higher probability of stress persistence, requiring complementary policies beyond vegetation enhancement. These insights also proved that one-size-fits-all often fails, and evidence-based policies are key to tailored urban planning.
- **Multidimensional urban planning**: besides evidence-based and more tailored urban planning and design, a key to helping cities anticipate underperforming interventions before implementation, policy actions need to be co-designed. For instance, green infrastructure should be co-designed with urban density, social dynamics, and mobility infrastructure to maximize mental health benefits; or bluespaces should go along with pedestrian-friendly environments for more comprehensive stress reduction.

In brief, this study reinforces the importance of data-driven scenario analysis in urban health planning. The results indicate that while green policies can significantly reduce stress, their success depends on urban density, social factors, and complementary infrastructure. Scenario Discovery provides policymakers a powerful, adaptive planning tool to create more resilient and health-conscious cities.

The developed Scenario Discovery demonstrates robustness and should be extended to analyze additional urban features in future applications, such as infrastructure changes (e.g., roads, streets) and transport modes, which are fundamental to city functioning. In the context of policy analysis, the model can contribute to:

- Validating the impact of policy actions, such as modifications in urban design, on stress reduction and well-being across different urban settings.
- Determining the necessary scale of a policy intervention to effectively mitigate stress and enhance well-being.
- Identifying key risk factors that may hinder policy effectiveness.

We advocate for the increased adoption of robust decision making methods and scenario discovery as support tools in the urban planning process towards, thus aiming at policies that are data-driven, targeted, and capable of fostering robust healthier cities.

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