eMOTIONAL Cities

Mapping the cities through the senses of those who make them

DELIVERABLE 6.1

Report on the indicators characterizing the built environment I and Measures on physical/mental health of people I

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Executive summary

This document consists of deliverable 6.1: “Report on the indicators characterizing the built environment I and measures on physical/mental health of people I”, that belongs to “WP6 – Evidence-based knowledge” of the *e*MOTIONAL Cities project, and it’s part of the “Task 6.1 - Identification of the urban artefacts that mostly affect indicators of physical and mental health”. The report is designed to set up, and shed light, on the urban metrics that will be quantified/analyzed to build evidence-based knowledge on how the built environment impacts people’s mental health and well-being. These metrics build on the indicators demonstrated in the report “D4.1 - Portfolio of variables, metrics and methods for urban health”, related to contextual/geographical data were afterwards analyzed in order to identify the ‘hot spots’, and the work in progress in WP5 focused of the individual biological data, collected through the 5 experiments reported in the “D5.1- Protocol with methods and metrics for neuroscience experiments”. The purpose of this report is to identify a set of indicators and measures that can be used to evaluate the outcomes of different experiments to establish a correlation between urban environment ‘elements’ and people’s health. By looking at the range values of the indicators and measures, this will allow us to define thresholds and to have the first attempt to answer the research question: How much of the urban environment ‘element’ impact on people health. The indicators and measures are organized according to the table below as a template.

TEMPLATE for Metrics

Description	A short description of the indicator and measures.
Inputs (optional)	An identification of the data needed for the indicator/measures to be operational
Experiment	An identification of the experiment where the indicator and measure can be applied (cf. D5.1)
Threshold / Benchmark	An explanation on how the indicator and measure can be interpreted and if it can be suitable for benchmarking.

1. Introduction

1.1. Background

Data is critical to make informed, efficient, and knowledge-based decisions. Without data we could not make solid interpretations and arguments, and convert them into facts, produce ideas, create evidence, and build knowledge. Without data there isn't good diagnosis which in turn are key to derive tailored decisions towards sustainable solutions, reduce uncertainty and improve decisions efficiency. As a fact, there is a historical association between governments, businesses, science, and citizens using data as a tool to inform, empower, monitor, regulate, represent, and make sense of the world and complexity of the cities (Kitchin, 2014). We are living a turning-point regarding data, that goes from data scarcity to big data. Overwhelmed by the data deluge, more attention has been given to data producing and data provision, and in turn insufficient care has been dedicated to data sustainability, e.g. data that can be used today and updated in the future; data structured and semi-structured; data utility (meaningful data, as it can inform about specific system state - comply or not; under or above a certain threshold -, and comes with metadata associated); and data usability (which it means data with a purpose, that can be usable for different tasks and analytics to meet end-users and stakeholders needs).

There are different types of data, and data can vary in form (quantitative or qualitative); structure (structured, semi-structured and unstructured); source (captured, derived, exhaust, transient); producer (primary, secondary, tertiary, synthetic, crowdsourcing and citizen science data); type (indexical, attribute, metadata, supplementary) (Kitchin, 2014; Townsend, 2013). However, no matter whatever data type there is, as long as it is meaningful and trustworthy data, it is pivotal to inform better policymaking, reduce risks and uncertainty, improve services, guarantee organizations and institutions sovereignty, educated decision making, and to empower people in general.

The report on the indicators characterizing the built environment and measures on physical/mental health of people follows three rules of thumbs: data sustainability; data utility; and data usability. All together make up what can be called good-quality data. Policymakers and decision makers rely more and more on data to make informed decisions and increase policies efficiency.

Creating healthier and sustainable cities and communities and promoting citizens' wellbeing are a global pillar for policies set by the UN SDG and the WHO. To build robust evidence-based knowledge about how the urban built environment, where people spend most of their time, affects people's physical and mental health requires access to and use of meaningful data. A "data revolution" (Kitchin, 2014) is taking place where cities are adopting data-driven policies and data (anticipatory) government strategies (Maffei, et al., 2020). In this regard, it's worth to say that this report takes a step forward towards the project objectives, namely, to raise awareness and foster community empowerment by giving them access to data so they can take evidence-based activism in participatory public decisions regarding urban design.

1.2. Objectives

This report's main objective is to frame a set of measures that can act as indicators to evaluate and build evidence on how, and how much, the built environment can affect people's physical and mental health and well-being. More precisely, the selected scales and measures will be used to characterize mental health and wellbeing within the project during Experiment 1 ("Brain as predictor of emotional urban places), Experiment 2 ("Understanding the neural processing of urban space through naturalistic stimuli"), Experiment 3 ("Mobile sensing of stress and emotional effects of daily urban experience") and Experiment 4 ("Outdoor neuroscience experiments"). A detailed description of each of these experiments can be found in deliverable D5.1.

The measures are organized into domains, which in fact outlined the way in which this report is structured.

1.3. Report structure

The report is organized into 4 sections/domains that all together characterize the built environment and allow to measure the physical/mental health. 1) **Physical dimensions of the built environment** (the built environment itself is identified as a determinant of health and a stress factor - urban stressors); 2) **Physical and Mental health and Wellbeing** (health professionals are aware that urbanite lifestyle, and the way people interact and their exposure to the surrounding environment can trigger stress and anxiety, which can escalate to more severe mental health issues. To build evidence about it, there is a need to resort to psychology and neurosciences tools); 3) **Transport and mobility** (The way city dwellers choose to use time and space has much to do with mobility and transport modes, which in turn leads people to be exposed to different urban features and transport that can affect people's physical and mental health, and wellbeing); 4) **Environmental and climatic** (Human activities are the main driver of the environmental and climatic changes not only at global, but also at local scale level, and more precisely with impact at Human scale. Environmental metrics can be used to pinpoint locations with low environmental quality and where remedial action is required to improve the population's health).

The summary matrix it's a first attempt for a wrap up compilation of indicators and metrics - inspired by the variables and metrics identified on D4.1 and adapted considering D5.1 experiments -, in order to measure how, and how much, the built environment impacts on people's physical and mental health, and wellbeing. It presents a detailed description and experiment related information and it is organized by categories and metadata items.

2. Physical dimension of the built environment

2.1. Introduction and objectives

The built environment is a human-made multiscale space where people live, work, travel, and play on a daily basis. And the physical dimension of such an environment encompasses land, air, water, plants and animals, buildings, streets, and other constructed interventions that form the physical character of a community, and all the natural resources that provide our basic needs and opportunities for social and economic development. Therefore, the built environment itself is a determinant of health as it influences overall community health as well as individual perception, cognition, and behaviors and it impacts on health expenditures.

2.2. Metrics and description

2.2.1. Urban nature and topography

Normalized Difference Vegetation Index (NDVI)

Description	Normalized Difference Vegetation Index – quantifies the density of vegetation on the ground through the difference between visible and near-infrared reflectance of vegetation cover
Inputs	Multispectral satellite image
Experiment	Exp. 1 – Brain as predictor; Exp. 2 – UrbanVideos; Exp. 3 – Mobile App; Exp.4 – Outdoor; Exp. 5 - Clinical
Threshold/ Benchmark	Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Lastly, low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1)

Sq green spaces per inhabitants

Description	Measure of square meters of green spaces per number of inhabitants. According to the Urban Atlas Nomenclature (2018) it can be defined as: “MinMU 0.25 ha, Minimum width: 10 m Public green areas for predominantly recreational use such as gardens, zoos, parks, castle parks, cemeteries. Suburban natural areas that have become and are managed as urban parks. Forests or green areas extending from the surroundings into urban areas are

	mapped as "green urban areas" when at least two sides are bordered by urban areas and structures, and traces of recreational use are visible.
Inputs	Urban Green Spaces (UGS) can be derived from the Urban Atlas for standardization, or national governmental land use land cover project.
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp. 3 – Mobile App; Exp.4 – Outdoor
Threshold/ Benchmark	Accordingly, to the WHO (2012), a minimum of 9m2 UGS per inhabitant and an ideal of 50m2 per inhabitant.

Slope

Description	Measure of the steepness of a walking path (the height difference between two points along a walk)
Inputs	Digital Elevation Model (DEM)
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp. 3 – Mobile App; Exp.4 – Outdoor
Threshold/ Benchmark	• <5%—Suitable • 5% < *x* < 8%—Acceptable • >8%—Inappropriate

2.2.2. Urban configurations and urban features

Walkability index

Description	Walkability is a measure of how friendly an area is to walk; walkability supports community health, safety, livability, and reduced car dependence. It describes to which extent a neighborhood is walkable
Inputs	The walkability index score is derived from physical characteristics of the urban environment that support walking including residential density, sidewalk presence and completeness, land use mix, retail floor space ratio, and intersection density
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp. 3 – Mobile App; Exp.4 – Outdoor; Exp. 5 - Clinical
Threshold/ Benchmark	Score below 25 is car-dependent; score between 50 to 69 is somehow walkable, and above 70 is very walkable.

Connectivity index

Description	measure of the number of nodes in regard with the edges linking them, accordingly to a planar graph metrics.
Inputs	Street network
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp.4 – Outdoor; Exp 5 - Clinical
Threshold/ Benchmark	There are several techniques for assessing the connectivity of a subdivision or municipality. Two of the most common are the U.S. EPA's methodology contained in the 2002 Indicator Dictionary – Smart Growth Index and the Link-Node approach outlined by Reid Ewing's book 1996 Best Development Practices. EPA's methodology relates the number of intersections in an area to the number of intersections plus the number of cul-de-sacs and dead-end streets. The number of intersections is divided by the sum of intersections and cul-de-sacs/dead ends/stub streets, giving a total possible score of 1.0 in areas where there are no cul-de-sacs/dead ends/stub streets. An index of 0.75 or higher is recommended to provide adequate connectivity. Under the Link-Node methodology, the number of links (sum of segments between intersections on through streets and cul-de-sacs in a system) is divided by the number of nodes (intersections and cul-de-sac ends). A perfect grid system would have an index of 2.5. Several municipalities have adopted indices of between 1.2 and 1.4 as the minimum desirable range for acceptable connectivity.

Diversity index

Description	Shannon-Wiener index adaptation to measure diversity through urban legal activities which means functional diversity. The diversity index in urban design stands as a proxy for vibrant streets.
Inputs	The diversity index is calculated based on the number of POI (retrieved via Geofabrik downloads website) - which includes cafes, restaurants, churches, theaters, monuments, hotels, parks, etc.), and third places which aren't places where people live (first place), nor a place where people work (second place), rather places where people carry out social activities (mainly social) which indicates places of social interaction -, per specific feature, e.g. street buffer area.
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp.4 – Outdoor; Exp5 - Clinical
Threshold/ Benchmark	normalized on a scale of values from 0 to 1, where 0 represents absence of diversity, and 1 stands for maximum diversity.

Complexity index

Description	The complexity of an urban scene or feature in the context of urban design is associated with positive/good and negative/bad stress (distress) impact on dwellers. The concept derives from the term fractals, introduced by Benoit Mandelbrot in 1977, which has been

	used to understand and measure complexity in many fields, including architecture and city planning. Here we measure street complexity based on buildings façades visual architecture adopting a quantitative method of box-counting.
Inputs	buildings façades geometries
Experiment	Exp. 2 - Urban/Videos; Exp. 5 - Clinical
Threshold/ Benchmark	Complexity index range values varies from 1 (low fractal dimension) to 2 (high fractal dimension)

ISOVIST (or Viewshed)

Description	The volume of space visible from a given point in space. It describes the space from the viewpoint of individuals as they perceive, interact with, and move through space.
Inputs	landscape and observer points
Experiment	Exp. 2 - Urban/Videos; Exp. 5 - Clinical
Threshold/ Benchmark	binary 0 - nonvisible; 1 - visible

2.2.3. Social and built-up urban densities

Population density

Description	A ratio of number of inhabitants per area. It is a measure that can be used to classify urban/rural territories and/or different degrees of urbanization.
Inputs	Number of inhabitants and area size
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp.4 – Outdoor
Threshold/ Benchmark	The degree of urbanization typology for Local Administrative Units level 2 (LAU2) - the typology of clusters starts by classifying grid cells of 1 km2 to one of the three following clusters, according to their population size and density: ● High-density cluster/urban center: contiguous grid cells of 1 km2 with a density of at least 1 500 inhabitants per km2 and a minimum population of 50 000; ● Urban cluster: cluster of contiguous grid cells of 1 km2 with a density of at least 300 inhabitants per km2 and a minimum population of 5 000. ● Rural grid cell: grid cell outside high-density clusters and urban clusters. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Degree_of_urbanisation_classification_-_2011_revision#Degree_of_urbanisation_classification.

Evenness index

Description	It's an entropy index - measure of "evenness"—the extent to which groups are evenly distributed among organizational units. The most widely used measure of residential evenness is the index of dissimilarity. It measures departure from evenness by taking the weighted mean absolute deviation of every unit's minority proportion from the city's minority proportion, and expressing this quantity as a proportion of its theoretical maximum
Inputs	Number of people belonging to minority groups
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp.4 – Outdoor
Threshold/ Benchmark	This index varies between 0 and 1.0, and, conceptually, it represents the proportion of minority members that would have to change their area of residence to achieve an even distribution

Floor area ratio (FAR)

Description	Floor Area Ratio (FAR) indicates the correlation between the plot area on which the building is constructed and the building floor area that can be used or is allowed to be used. A higher floor area ratio implies an urban or denser construction.
Inputs	Building area and Lot area. Floor Area Ratio (FAR) = Total Building Floor Area / Gross Lot Area
Experiment	Exp. 1 – Brain as predictor; Exp. 2 - Urban/Videos; Exp.4 – Outdoor
Threshold/ Benchmark	Not applicable as Ratio varies depending on the population density, construction-related activities, growth patterns, and the nature of the building's space or land.

3. Physical and mental health and wellbeing

3.1. Introduction and objectives

Mental health and wellbeing are essential components of a thriving society, and they play a critical role in urban policymaking. With an increasing number of people living in cities worldwide, it has become more important than ever to prioritize mental health and wellbeing in urban planning and policymaking. The rapid pace of urban development, coupled with the pressures of modern life, can also contribute to stress and anxiety, which can further exacerbate mental health issues. To assess physical and mental health and wellbeing, this section is introducing the measures and metrics to benchmark and quantify the psychology and neuroscience related metrics.

3.2. Metrics and description

Several different scales and physiological measures will be evaluated for the characterization of mental health and wellbeing during the experiments. These are divided into different categories: Mental Health, Personality and Affect, Neuropsychological/Cognitive and Wellbeing.

3.2.1. Mental Health

Depression, Anxiety and Stress Scale (DASS-21)

Description	A (baseline) measure of the emotional states of **depression**, **anxiety,** and **stress** of participants.
Inputs (optional)	A set of three self-report scales.
Experiment	Exp 1 and 2 - Brain as Predictor, Exp. 3 - Mobile App, Exp. 4 - Outdoor
Threshold / Benchmark	Depression: normal (0-9); mild/moderate (10-20); severe (>21) Anxiety: normal (0-7); mild/moderate (8-14); severe (>15) Stress: normal (0-14); mild/moderate (15-25); severe (>26)

Geriatric Depression Scale (GDS)

Description	A (baseline) measure of **depressive symptoms in the older population** (that can be used in mild cognitive impaired subjects).
Inputs (optional)	A 30-item self-report scale.
Experiment	Exp. 5. Clinical
Threshold / Benchmark	Normal (0-10); Mild depressive symptoms (11-20); Moderate to severe depressive symptoms (21-30)

6-Item Bergen Social Media Addiction Scale

Description	A (baseline) assessment of participant's **problematic social media use.**
Inputs (optional)	A 6-item self-report scale.
Experiment	Exp 1 and 2 - Brain as Predictor, Exp. 3 - Mobile App, Exp. 4 - Outdoor
Threshold / Benchmark	A score of 24 has been seen as a clinical cut-off point for a disorder (the score of 19 has also been suggested but as an empirical cut-off).

3.2.2. Personality and Affect

HEXACO – Honesty-Humility / Emotionality / Conscientiousness Domain

Description	A (baseline) assessment of participant's three **personality dimensions** relevant for the interaction with the urban environment: **Honesty-Humility** (tendency to be fair, genuine or cooperative with others – relevant due to the urban social determinants of health); **Emotionality** (tendency to respond worse to stress, need of support from others – relevant due to the importance to urban stressors); and **Conscientiousness** (tendency to be show self-discipline, planned behavior and efficiency – relevant to control for individual characteristics when dealing with urban exposure) – as part of the broader HEXACO personality inventory.
Inputs (optional)	A set of three self-report personality domains.
Experiment	Exp 1 and 2 - Brain as Predictor, Exp. 3 - Mobile App, Exp. 4 - Outdoor
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Behavioural Activation and Behavioural Inhibition Scale (BAI)

Description	A (baseline) assessment of participants regarding two general motivational systems that underlie behavior and affect: the **behavioral inhibition** system (BIS) or motivation to avoid aversive outcomes; and the **behavioral activation** system (BAS) or the motivation to approach goal-oriented outcomes.
Inputs (optional)	A 24-item self-report scale.
Experiment	Exp 1 and 2 - Brain as Predictor, Exp. 4 - Outdoor
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Positive and Negative Affect Score (PANAS)

Description	A (baseline) measure of participants in regard to two mood scales: **positive affect** (PA) or the extent to which a person feels interested, excited, strong, enthusiastic, proud, alert inspired, determined, attentive, and active; and **negative affect** (NA) or descriptors such as stressed, upset, guilty, scared, hostile, irritable, ashamed, nervous, jittery, and afraid.
Inputs (optional)	A 20-item self-report scale.
Experiment	Exp 1 and 2 - Brain as Predictor, Exp. 4 - Outdoor

Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

3.2.3. Neuropsychological/Cognitive

Mini Mental State Examination (MMSE)

Description	A (baseline) global measure of the **clinical cognitive state of older adults** (and a screening tool for mild cognitive impairment identification), through the evaluation of several function such as attention and orientation, memory, registration, recall, calculation, language and ability to draw a complex polygon.
Inputs (optional)	A 30-question neuropsychological assessment.
Experiment	Exp. 5 - Clinical
Threshold / Benchmark	Cognitive impairment is considered if <16 for illiterate subjects; <23 for those with eleven years of less of education; <28 for those with more than eleven years of education.

Wechsler Memory Scale

Description	A (baseline) neuropsychological assessment designed to measure verbal and non-verbal (visual, working and recognition) **memory abilities in adults**.
Inputs (optional)	Neuropsychological subtests of the battery will be applied.
Experiment	Exp. 5 - Clinical
Threshold / Benchmark	Low scores indicate poorer cognitive performance than expected (for age and education level).

3.2.4. Physiological

Galvanic Skin Response (GSR)

Description	A transient variation of the electrical properties (i.e., conductance) of the skin (which is consequence of sweat glands and blood flow activation), being a peripheral and objective indicator of **emotional arousal** in response to a stimulus.
Inputs (optional)	An Empatica wristband device signal of an EDA sensor sampled at 4Hz.

Experiment	Exp. 2 - Brain as a predictor, Exp. 3 - Mobile App, Exp. 4 - Outdoor and Exp. 5 - Clinical
Threshold / Benchmark	(High GSR is associated with higher emotional arousal, usually elicited by novel, with cognitive/attentional load or emotionally significant events/stimuli; influenced by the demographic and physical characteristics of the study subjects, as well as by the environmental conditions during the recordings)

Heart Rate Variability (HRV)

Description	The variation among a set of temporally ordered inter heartbeat intervals, which reflect the degree to which cardiac activity can be modulated by stimuli to meet changing situational demands – being related to **emotional arousal** and wellbeing.
Inputs (optional)	An Empatica wristband device signal obtained by photoplethysmography at 64Hz, measuring Blood Volume Pulse (from which heart rate and inter beat interval is derived).
Experiment	Exp. 2 - Brain as a predictor, Exp. 3 - Mobile App, Exp. 4 - Outdoor and Exp. 5 - Clinica
Threshold / Benchmark	(High HRV is associated with higher emotional wellbeing, including being correlated with lower levels of worry, lower anxiety, and better regulated emotional responding; influenced by the demographic and physical characteristics of the study subjects, as well as by the environmental conditions during the recordings).

Functional Magnetic Resonance Imaging (fMRI Activity)

Description	Brain activation (reflecting localized changes in brain blood flow and blood oxygenation – BOLD effect) during exposure to urban images in certain regions of interest (ROIs).
Inputs (optional)	Imaging data acquired on a 3-T MRI scanner
Experiment	Exp.1 - Brain as a predictor
Threshold / Benchmark	(Greater stimulus-evoked positive BOLD in a certain area of the brain is associated with increased activation or involvement).

Valence (Starlab EEG Feature)

Description	Valence is defined in the pleasure-displeasure continuum, as being more or less positive. It is calculated as result of a Starlab's internal work based in the representation of emotions in a 2D space of valence and arousal using a combination of alpha and gamma asymmetries (Muller et al., 1999[s1]; Koelstra et al., 2012[s2]).
Inputs (optional)	EEG Data acquired from an Enobio 32 at 500Hz

Experiment	Exp. 2 - Brain as a predictor, and Exp. 4 - Outdoor
Threshold / Benchmark	(An increase in the percentage of change of this descriptor is associated with an increase of pleasure and positivity.)

Arousal (Starlab EEG Feature)

Description	Arousal refers to the general level of alertness and wakefulness of a person. It is calculated as a result of Starlab's internal work based in the representation of emotions in a 2D space of valence and arousal using a normalized combination of frontal theta and beta rhythms (Harmon-Jones et al., 2003[s3]; Chanel et al., 2006[s4])
Inputs (optional)	EEG Data acquired from an Enobio 32 at 500Hz
Experiment	Exp. 2 - Brain as a predictor and Exp. 4 - Outdoor
Threshold / Benchmark	(An increase in the percentage of change of this descriptor is associated with an increase of alertness and wakefulness.)

Cognitive Workload (Starlab EEG Feature)

Description	Cognitive Workload is the level of cognitive engagement needed for learning; if it is too high it can negatively affect performance (So et al., 2017[s5]). It is defined as a descriptor that measures the level of cognitive processes from the domain of executive functions. It increases with working memory and level of difficulty of problem-solving tasks. It is often described as the ratio of theta power and alpha power (Gevins et al., 1991[s6])
Inputs (optional)	EEG Data acquired from an Enobio 32 at 500Hz
Experiment	Exp. 5 - Clinical
Threshold / Benchmark	(An increase in the percentage of change of this descriptor is associated with an increase of working memory and mental effort.)

Fatigue (Starlab EEG Feature)

Description	Fatigue is defined as a decrease in alertness level that can impair efficiency, performance and memory retrieval (Stern et al., 1994[s7]); will be assessed using a temporal ratio between low and high frequencies (Lal et al., 2001[s8] ; Jap et al., 2009[s9]).
Inputs (optional)	EEG Data acquired from an Enobio 32 at 500Hz
Experiment	Exp. 5 - Clinical
Threshold / Benchmark	(An increase in the percentage of change of this descriptor is associated with an increase of fatigue)

Attention (Starlab EEG Feature)

Description	Attention is defined as a state of focused attentional processing, concentration, persistent focus across time. It will be assessed by the theta frontal midline (Klimesch, 1999[s10]).
Inputs (optional)	EEG Data acquired from an Enobio 32 at 500Hz
Experiment	Exp. 5 - Clinical
Threshold / Benchmark	(An increase in the percentage of change of this descriptor is associated with an increase of attention)

3.2.5. Psychological wellbeing and other wellbeing-related

Psychological Wellbeing Scale (PWB)

Description	A (baseline) measure of participant’s **psychological wellbeing** and happiness that is focused on six distinct components: autonomy, environmental mastery, personal growth, positive relations with others, purpose in life and self-acceptance.
Inputs (optional)	A shortened 18-item self-report scale.
Experiment	Exp. 2 - Brain as predictor, Exp. 3 - Mobile App, Exp. 4 - Outdoor, and Exp. 5 - Clinical
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Satisfaction with Life Scale (SWLS)

Description	A (baseline) measure of participant’s global cognitive judgment of overall **satisfaction with their life**.
Inputs (optional)	A 5-item self-report scale.
Experiment	Exp. 1 - Brain as a predictor
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Short Mood Scale (SMS)

Description	A (ecological momentary) assessment of participant’s affective states along dimensions of **valence, arousal and calmness**.
Inputs (optional)	A 6-item self-report scale.
Experiment	Exp. 3 - Mobile App

Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Karolinska Sleepiness Scale (KSS)

Description	A (daily) measure of participant's **subjective levels of sleepiness** in adults during their daily routine.
Inputs (optional)	A single question that asks the individual to rate their current level of sleepiness.
Experiment	Exp. 3 - Mobile App
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

4. Transport and mobility domain

4.1. Introduction and objectives

Observing and analyzing individuals' mobility and activities choices are also essential for understanding the impact of different urban features on individuals' physical and mental health. This is so because the individual exposure to different urban elements is conditional to the spaces where they travel around and/or stay for performing some activities. Moreover, different modes will expose individuals to diverse features of the transportation system (e.g., traffic conditions for motorized modes, walking infrastructure for pedestrians), while having inherent characteristics (e.g., active modes promote physical activity) that can affect their physical and mental well-being.

Under the hypothesis that collecting and coupling mobility-related indicators with physiological measures can uncover how the travels and activities performed by an individual impact his/her physical and mental health, this project will conduct an experiment to collect mobility and biosensor data simultaneously. Such data is vital for the design of adequate and sustainable policies, as decision-makers strongly depend on the evidence available to them. Moreover, by bringing the focus to citizens and how their mobility choices influence their well-being, we will be able to not only inform the design of policies to maximize welfare, and public health impacts, but also to engage/empower citizens (society) for tackling public health problems.

This sub-section will present the mobility measures that will be collected and used to characterize the mobility behavior of individuals within the project. More specifically, these measures will be collected during Experiment 3 ("Mobile sensing of stress and emotional effects of daily urban experience"), from which the reader can find a detailed description in the deliverable D5.1.

4.2. Metrics and description

4.2.1. Individual Attitudes and Planning towards Transport

Attitude towards transport

Description	The scale is a self-report measure of **individuals' attitudes towards different transport modes**. It measures individuals' attitudes according to their level of agreement with twenty statements about how they perceive their mobility and the usage of different transport modes. It uses a to measure responses, ranging from "strongly disagree" to "strongly agree."
Inputs (optional)	A 5-point Likert scale
Experiment	Exp. 3 - Mobile App
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Activity planning: This variable will store information on changes in planned activities (e.g., changes in location and/or time). It is a self-reported information by each individual collected at the end of each day through a smartphone application.

4.2.2. Level of Service

Travel time

Description	It is a measure of how long it takes to travel between an origin and a destination location. This variable can be discretized by other variables (e.g., mode, activity at the destination location, time of the day - peak or off-peak). The variable can also be decomposed into waiting time, in-vehicle travel time, out-of-vehicle travel time for a given trip.
Inputs (optional)	A trajectory with visited geographical coordinates from location services (e.g. GPS, cellular data…)
Experiment	Exp. 3 - Mobile App. It will be measured for each individual, and each trip for 14 days, using location and time data from the smartphone application.
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Travel distance

Description	It is a measure of how long it takes to travel between an origin and a destination location. This variable can be discretized by other variables (e.g., mode, activity at the destination location, time of the day - peak or off-peak). The variable can also be decomposed into in-vehicle travel distance and out-of-vehicle travel distance for a given trip.
Inputs (optional)	A trajectory with visited geographical coordinates from location services (e.g. GPS, cellular data…)
Experiment	Exp. 3 - Mobile App. It will be measured for each individual, and each trip for 14 days, using location and time data from the smartphone application.
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Public Transport Accessibility

Description	It refers to the walking distance to the nearest public transport stop / station. It will be a measure derived from the residential location of each individual and the location of realized activities, according to the location data collected from the smartphone application.
Inputs (optional)	A single question asking the residential addresses; or activity locations inferred from daily trajectories (from location services, e.g. GPS, cellular data…)
Experiment	Exp. 3 - Mobile App. It will be measured for each individual, and each detected activity for 14 days, using location and time data from the smartphone application.
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

4.2.3. Travel Patterns

Mode usage

Description	Categorical variable, with finite set of labels. This variable refers to the mode used for individuals to perform each stage/leg of their trips. The categories of modes considered are: car, walk, taxi/transport app, bus, metro, train, motorcycle, bicycle, scooter or other.
Inputs (optional)	It will be measured for each individual, and each trip leg for 14 days, using the trajectory/location data from the smartphone application, which allows for inference of the mode used (algorithms). Also, the inferred mode can be confirmed or corrected by the

	individual for which the trip was made, directly on the smartphone app.
Experiment	Exp. 3 - Mobile App. It will be measure for each individual, and each detected activity for 14 days, using location and time data from the smartphone application.
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Activity Purpose

Description	Categorical variable, with finite set of labels. This variable refers to the purpose of the activities performed by each individual during the day. The categories of activities considered are: work, education, shopping, leisure, personal and escort.
Inputs (optional)	It is self-reported information by each individual collected in a single question for each identified pair of trip-activity, through a smartphone application. The identification of an activity is performed using the trajectory/location data from the smartphone application (algorithms), to which the subject needs to add the purpose label.
Experiment	Exp. 3 - Mobile App. It will be measured for each individual, and each detected activity for 14 days.
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

Activity locations

Description	Latitude and longitude refer to the locations where individuals stopped to perform activities. It allows for recreating the activity-space representation of mobility for each individual.
Inputs (optional)	It will be measured for each individual, and each trip leg for 14 days, using the trajectory/location data from the smartphone application, which allows for inference of the mode used (algorithms). Also, the inferred activity location can be confirmed or corrected by the individual for which the trip was made, directly on the smartphone app.
Experiment	Exp. 3 - Mobile App. It will be measured for each individual, and each detected activity for 14 days.
Threshold / Benchmark	(Not applicable as the scores varies across populations or samples; being rather used as control or confounding variable)

5. Environmental and Climatic domain

5.1. Introduction and objectives

Human activities are the main driver of environmental and climatic changes on our planet. Urban systems strongly affect the environment, and the environment shapes the way people interact within it. Measuring and quantifying the effects of urban systems on the environment and on public health requires the use of environmental metrics: they allow to generate fundamental information on the quality of air, water, soil, and other components, as well as on the quantity of trash produced and the levels of energy use.

Environmental metrics can be used to pinpoint locations with low environmental quality and where remedial action is required to improve the population's health. They enable policymakers and urban planners locating actions to promote health and direct the implementation of successful policies to reduce the adverse effects of urbanization on the environment. Measuring and monitoring environmental quality has already generated novel data sources, sensors, and computing methods that have led to a paradigm shift in urban analyses, significantly expanding research questions directed at the urban level and its residents. This shift includes tackling challenges of the Anthropocene, including climate change, urban overheating, poor air quality, and climate injustice. Particularly, these tools and methods have led to comprehensive analyses of the dynamics of urban systems and human-environment interactions at fine temporal and spatial scales.

A future objective is to generate interdisciplinary knowledge spanning a wide range of expertise which allows more complex, solutions-oriented analyses from health sciences to social justice and equity. The following section lists the selected metric for the domain of environment and climate that will be used to benchmark these phenomena within the relevant experiments and analysis.

5.2. Metrics and description

Perceived Temperature - Universal Thermal Climate Index (UTCI)

Description	The Universal Thermal Climate Index (UTCI) is a measure of the combined effects of temperature, humidity, wind speed, and radiation on the human body. It was developed by an international group of researchers as a tool to assess thermal comfort and heat stress, and to evaluate the potential impact of climate change on human health. The UTCI takes into account both the physical parameters of the environment and the physiological response of the human body, such as sweating and heat exchange. It is based on a model that simulates the heat transfer between the human body and the surrounding environment and uses standard meteorological data as input. The metric is increasingly used by public health authorities, urban planners, and emergency services to assess the risks associated with heat waves and extreme weather events, and to design strategies to mitigate their impact on vulnerable populations.
Inputs	Air Temperature, Relative Humidity, Mean Radiant Temperature, Wind Speed
Experiment	Exp.4 - Outdoor
Threshold / Benchmark	The metric defines perceived temperatures between 9 to 26 °C as a comfort range.

Local Climate Zones (LCZ)

Description	Local Climate Zones (LCZ) are a classification system that divides urban areas into distinct zones based on their physical and thermal properties. This system was developed by a team of researchers to support the study of urban heat islands and their impact on human health and well-being in cities. It divides urban areas into 17 different zones, based on land use, surface cover, and the nature of the built environment. These zones range from densely built-up areas with little vegetation, to open green spaces and bodies of water. It also takes into account the size and shape of urban features, such as building height, street orientation, and the presence of trees and other shading elements. The LCZ system is used to map urban areas and identify areas of high urban heat island intensity, which can help guide urban planning and design strategies aimed at reducing the heat island effect and improving human comfort and well-being. It can also be used to study the impact of urban heat islands on energy consumption, air quality, and other environmental factors. Overall, this measure provides a standardized framework for characterizing the physical and thermal properties of urban areas, which is important for developing effective strategies to mitigate the negative impacts of urbanization on human health and the environment.
Inputs	N/A
Experiment	Exp.4 - Outdoor
Threshold / Benchmark	N/A

Sky View Factor (SVF)

Description	Sky view factor (SVF) is a measure to quantify the amount of visible sky when standing at a particular point in a given urban environment. It is typically expressed as a ratio of the visible sky area to the total visible area from a given point. This measure is used in urban planning and design to assess the amount of direct sunlight and solar radiation that reaches a particular area. It can also be used to estimate the cooling effect of natural ventilation, and to evaluate the potential for urban heat island mitigation strategies based on morphology of the city. Sky view factor is influenced by the geometry of the built environment, including the height and spacing of buildings, the location of trees and other vegetation, and the presence of other physical features that obstruct or reflect sunlight. This metric is an important tool for understanding the impact of the built environment on urban microclimates, and for developing effective strategies to improve human comfort and well-being in urban areas.

Inputs	360° images
Experiment	Exp.4 - Outdoor
Threshold / Benchmark	N/A

Wind Exposure / Wind Comfort

Description	Wind comfort in urban environments refers to the level of comfort or discomfort that people experience because of wind driven by the urban artifacts. This metric also has an influence on the thermal comfort of people in outdoor spaces, as well as the dispersion of air pollutants and particles. Different wind patterns created by urban artifacts can influence the perception of wind by people in outdoor spaces in different seasons and times and can affect the occupancy of outdoor spaces for different activities, such as walking, cycling, or sitting. Urban planners and designers can use information about wind comfort to inform the design of outdoor spaces that are comfortable and usable for different activities and user groups.
Inputs	wind speed, wind gust
Experiment	Exp.4 - Outdoor
Threshold / Benchmark	There are several wind comfort criteria's that could be used in this project based on the availability of the data and computational capacities. These metrics are Lawson criteria, Davenport Criteria, NEN 8100 Criteria which takes into account the annual statistics and frequencies.

Urban Heat Island Effect (UHI)

Description	The Urban Heat Island (UHI) is a phenomenon that occurs when an urban area experiences higher temperatures than surrounding rural areas. It is caused by a combination of factors, including the high density of buildings, roads, and other infrastructure in cities, the absorption and re-radiation of heat by urban surfaces, and the release of heat from human activities, such as transportation and industry. Urban heat islands can have a range of negative impacts on human health and the environment. For example, they can increase the incidence of heat-related illnesses, such as heat stroke and dehydration, and exacerbate air pollution problems by increasing the formation of ground-level ozone and other pollutants. They can also have negative impacts on ecosystems, by altering the timing of seasonal events, such as plant growth and migration, and reducing the availability of water for plants and animals. This metric has been intensively used and applied in different cities as a measure to quantify the effects of urbanization and the necessity of balancing built and natural surfaces in cities.
Inputs	Urban surfaces
Experiment	Exp.4 - Outdoor
Threshold / Benchmark	N/A

Air Quality / Air Pollution Exposure

Description	Air quality in cities is a metric used to measure the level of exposure that individuals or populations have to air pollutants in urban areas. Air pollution is a major public health concern, and exposure to high levels of air pollutants has been linked to a range of adverse health outcomes, including respiratory diseases, cardiovascular diseases, and cancer. Air pollution exposure can be measured in a variety of ways, including by the concentration of specific pollutants, such as particulate matter, nitrogen oxides, and ozone, or by using composite indices, such as the Air Quality Index (AQI), which takes into account multiple pollutants and provides a single metric for assessing air quality.
Inputs	Air
Experiment	Exp.4 - Outdoor

Threshold / Benchmark	Metrics concerning the particulate matter such as PM10 and PM2.5 driven by transportation, industrial activities. the threshold for these exposures based on WHO recommendations For PM10, a 24-hour average limit of 50 (µg/m³) and an annual average limit of 20 µg/m³. For PM2.5, a 24-hour average limit of 25 µg/m³ and an annual average limit of 10 µg/m³. These measures will be applied based on the availability of data. It is important to note that different countries and regions have different air quality standards and regulations, depending on local conditions and priorities.

Noise Exposure / Pollution

Description	Noise pollution in urban environments refers to the presence of excessive or unwanted noise that can negatively affect human health and well-being. Urban areas are often characterized by high levels of noise pollution, due to a range of sources, including traffic, construction, industrial activity, and entertainment venues. Exposure to high levels of noise pollution can have a range of negative effects on human health and well-being.
Inputs	Noise Level
Experiment	Exp.4 - Outdoor
Threshold / Benchmark	WHO recommends that outdoor noise levels should not exceed an average of 70 decibels (dB) over a 24-hour period, and an average of 53 dB during the night.

6. Final Remarks

This report presents the first deliverable of the WP6 – Evidence-based knowledge and follows on the ongoing work related to the Task 6.1 “Identification of the urban artefacts that mostly affect indicators of physical and mental health”. Here we identified, described, characterized, and explained the set of urban metrics according the psychological and neuroscience experiments and in order to discover which environment and urban features influence more subjects’ cognitive performance and emotional states.

We also want to underline that’s this report on the indicators characterizing the built environment and measures on physical and mental health of people consists of three parts report, e.g. D6.1 (the one its presented now); D6.3 (“Report on the indicators characterizing the built environment II”), and D6.4 (“Report on the measures on physical/mental health of people II”), that will be deliverable in month 30 and month 38 respectively, which will detailed more on the indicators and measures derived from the urban cases as well the preliminary results of the experiments from WP5.

The listed indicators and measure will be applied to different experiments explained in this report and they will be refined based on the applicability of each depending on the characteristics of the datasets. Therefore, the listed indicators and measures will be updated, based on availability of data, in the following tasks of the WP6.

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ANNEX I. SUMMARIZED TABLE OF INDICATORS AND METRICS

Metric	Description	Focus Subjects (BE/MW/MO/CL)	Sub-Domain	Inputs	Reference	Use Cases / Application Scenarios								Spatially Dynamic	Temporally Dynamic	Spatial Resolution	Temporal Resolution	Vulnerable groups	Age	Gender	Self Reporting	Influenced by Experiment	Processing Methodology
						Exp 1 Brain as predictor	Exp 2 Brain as predictor	Exp 3 App	Exp 3 Lab	Exp 4 Outdoor	Exp 5 Clinical	Agent Based Modeling	Policy Making										
DASS-21	Depression, Anxiety and Stress Scale. 21 items. 5-10 minutes completion time.	MW	MENTAL HEALTH		Lovibond, P. F. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. Behaviour research and therapy, 335-343.	x	x	x		x				No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
GDS	Geriatric Depression Scale. Adult depression scale, composed of 30 items. 5-7 minutes completion time.	MW			Scogin, F., Rohen, N., & Bailey, E. (2000). Geriatric Depression Scale. In M. E. Maruish (Ed.), *Handbook of psychological assessment in primary care settings* (pp. 491–508). Lawrence Erlbaum Associates Publishers.						x			No	No	-	-	Yes	Yes	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Hamilton Anxiety Scale?		MW									x			No	No								
BAS/BIS	To gauge the approach/withdrawal behaviour of the volunteers before task engagement	MW	MOTIVATIONAL			x	x			x				No	No			No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Social media usage	Estimates how many hours per day volunteers spend on social media platforms. They would respond on a 7-point scale (1 = less than an hour; 7 = six or more hours) (Meshi et al., 2020).	MW	SOCIAL MEDIA					x															
6-item Bergen Social Media Addiction Scale	Problematic social media would be assessed. Each item would assess a core aspect of addiction: preoccupation, mood modification, tolerance, conflict, withdrawal, and relapse. Less than 5min completion time.	MW			Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. (2016). The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychology of Addictive Behaviors, 30* (2), 252–262.	x	?	x						No	No	-	-	No	Yes	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Hexaco - Emotionality domain - Anxiety scale (8 items) -	Assesses a tendency to worry in a variety of contexts. Low scorers feel little stress in response to difficulties, whereas high scorers tend to become preoccupied even by relatively minor problems.	MW	PERSONALITY		Lee, K., & Ashton, M. C. (2018). Psychometric properties of the HEXACO-100. Assessment, 25, 543-556.	x	x	x		x				No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Hexaco - Conscientiousness domain - Prudence scale (8 items) -	Assesses a tendency to deliberate carefully and to inhibit impulses. Low scorers act on impulse and tend not to consider consequences, whereas high scorers consider their options carefully and tend to be cautious and self-controlled.	MW					x	x						No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Hexaco - Honesty-Humility domain - (10 items) -	Persons with very high scores on the Honesty-Humility scale avoid manipulating others for personal gain, feel little temptation to break rules, are uninterested in lavish wealth and luxuries, and feel no special entitlement to elevated social status. Conversely, persons with very low scores on this scale will flatter others to get what they want, are inclined to break rules for personal profit, are motivated by material gain, and feel a strong sense of self-importance.	MW					x	x						No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Positive and negative affect score (PANAS)	Assesses the affective state of the volunteers at the time of evaluation.	MW	AFFECT			x	x			x				No	No			No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Satisfaction with Life scale (SWLS)	Developed to assess satisfaction with the respondent's life as a whole (5-item)	MW	WELL-BEING			x	x	x		x				No	No			No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
			NATURE?																				
MMSE	Mini-Mental State Examination. 30-item questionnaire. Widely used test of cognitive function among the elderly. 5-10 minutes completion time.	MW	NEUROPSYCH		Arevalo-Rodriguez, I., Smailagic, N., Roqué I Figuls, M., Ciapponi, A., Sanchez-Perez, E., Giannakou, A., Pedraza, O. L., Bonfill Cosp, X., & Cullum, S. (2015). Mini-Mental State Examination (MMSE) for the detection of Alzheimer's disease and other dementias in people with mild cognitive impairment (MCI). The Cochrane database of systematic reviews, 2015(3), CD010783. https://doi.org/10.1002/14651858.CD010783.pub2						x			No	No	-	-	Yes	Yes	No	No	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Wechsler Memory Scale	Measures a number of different types of memory, including verbal, auditory, visual, short-term, and working memory. ~42 minutes completion time.	MW			Ryan, J. J., Kreiner, D. S., Gontkovsky, S. T., & Teichner, G. (2023). Wechsler memory scale-fourth edition (WMS-IV) in the neuropsychological evaluation of patients diagnosed with probable Alzheimer's disease. Applied neuropsychology. Adult, 1–8. Advance online publication.						x			No	No	-	-	Yes	Yes	No	No	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Subjective Memory Complaints											?										Yes		
Blessed Dementia Rating Scale	Clinical rating scale with 22 items that measure changes in performance of everyday activities (eight items), self-care habits (three items), and changes in personality, interests, and drives (11 items). Ratings are based on information from relatives or friends and concern behavior over the preceding six months 5-10min completion time.	MW			Erkinjuntti, T., Hokkanen, L., Sulkava, R., & Palo, J. (1988). The Blessed Dementia Scale as a screening test for dementia. International Journal of Geriatric Psychiatry, 3(4), 267-273.						x			No	No	-	-	Yes	Yes	No	No	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
N-back task	N-back task, used to measure working memory (WM).		COGNITIVE						x		?												

Metric	Description	Focus Subjects (BE/MW/MO/CL)	Sub-Domain	Inputs	Reference	Use Cases / Application Scenarios								Spatially Dynamic	Temporally Dynamic	Spatial Resolution	Temporal Resolution	Vulnerable groups	Age	Gender	Self Reporting	Influenced by Experiment	Processing Methodology
						Exp 1 Brain as predictor	Exp 2 Brain as predictor	Exp 3 App	Exp 3 Lab	Exp 4 Outdoor	Exp 5 Clinical	Agent Based Modeling	Policy Making										
Cortisol	Salivary cortisol levels. Indicative of emotional stress. Measured before vs. After exposure to acute stressor.	MW	PHYSIOLOGICAL		Hellhammer, D. H., Wüst, S., & Kudielka, B. M. (2009). Salivary cortisol as a biomarker in stress research. Psychoneuroendocrinology, 34(2), 163-171.				x					No	No	Lab	-	No	No	Yes	No	Yes	Outsourcing - level of salivary cortisol at certain time points (float). Processed with traditional statistical tests.
Legibility, Mystery, and Visual Access as predictors of preference and perceived danger in forest settings without pathways	Defines the predictors of the preference matrix that can be used to measure landscape aesthetics				(Herzog & Kropscott, 2004)	x																	
Perceived Restorativeness Scale	Gauges the four restorative qualities such as being away, fascination, extent, and compatibility		Online Survey		(Berto et al., 2005)	x	?																
Beauty ratings for the images of the urban spaces (5 point scale)	Obtains scenic beauty ratings for the images of the urban spaces					x																	
Liking assessment	5-star scale					x	?																
Familiarity assessment	5-star scale					x	?																
Safety assessment	5-star scale					x	?																
Affective slider	Emotion assessment - 2D					x	?																
Social?	?					x	?																
Attitude towards transports	Psychological scale. 20 questions (5-item scale). Less than 5min completion time.	MO	PERSONALITY		[Sonja]			X						No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
PWI Environmental Mastery	Psychological WellBeing Index - Environmental Mastery subscale (3 items).	MW	WELL-BEING		Ryff, C. D. (1995). The structure of psychological well-being revisited. Journal of personality and social			X						No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests /
PAD8	Participant-rated AD8. Brief dementia screening tool, sensitive to early cognitive change. Self-reported. 8 items. Less than 5min completion time.	MW	NEUROPSYCH		Galvin, J. E. (2007). Patient's rating of cognitive ability: using the AD8, a brief informant interview, as a self-rating tool to detect dementia. Archives of neurology, 725-730.			X						No	No	-	-	No	Yes	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
EMA/End of Day	Ecological Momentary Assessment. Based on Short Mood Scale (6 items) + social component + open text field	MO	WELL-BEING		Wilhelm, P., & Schoebi, D. (2007). Assessing mood in daily life: Structural validity, sensitivity to change, and reliability of a short-scale to measure three basic dimensions of mood. European Journal of Psychological Assessment, 23(4), 258.			X						Yes	No	GPS	-	No	No	No	Yes	Yes	Quantitative score. Processed with traditional statistical tests / linear regression models.
PSQI	Pittsburgh sleep quality index (PSQI) - 1 item - adapted (1-4 scale)	MW	WELL-BEING		Smyth, C. (1999). The Pittsburgh sleep quality index (PSQI). Journal of gerontological nursing, 25(12), 10-10.			X	X					No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
Restless Legs	1 item to screen for restless legs (affects sleep quality). Y/N scale.	MW	WELL-BEING		Ferri, R., Lanuzza, B., Cosentino, F. I., Iero, I., Tripodi, M., Spada, R. S., Toscano, G., Marelli, S., Aricò, D., Bella, R., Hening, W. A., & Zucconi, M. (2007). A single question for the rapid screening of restless legs syndrome in the neurological clinical practice. European journal of neurology, 14(9), 1016–1021. https://doi.org/10.1111/j.1468-1331.2007.01862.x			X						No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
KSS	Karolinska Sleepiness Scale - 1 item (1-9 scale)	MW	WELL-BEING		Shahid, A., Wilkinson, K., Marcu, S., & Shapiro, C. M. (2011). Karolinska sleepiness scale (KSS). In STOP, THAT and one hundred other sleep scales (pp. 209-210). Springer, New York, NY.				X					No	No	-	-	No	No	No	Yes	No	Quantitative score. Processed with traditional statistical tests / linear regression models.
EDA-ris. time	EDA=Electrodermal activity or SCR=skin conductance response. Refers to autonomic changes in the electrical properties of the skin, being a good indicator of arousal levels. The rise time corresponds to the time taken from SCR onset to reach peak amplitude within the SCR.	MW	Physiological Data		Silva, H., Fred, A., & Lourenco, A. (2012). Electrodermal response propagation time as a potential psychophysiological marker. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2012, 6756–6759. https://doi.org/10.1109/EMBC.2012.6347545			X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from EDA signal. Timeseries. Processed with any ML models
EDA-amp	Skin response amplitude. Skin conductance delta function, from SCR onset to the SCR peak.	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from EDA signal. Timeseries. Processed with any ML models
EDA-rec. time	Recovery time. The time it takes from skin conductance peak to 63% of the peak amplitude.	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from EDA signal. Timeseries. Processed with any ML models
IBI	Interbeat Interval (or RR interval).	MW			Shaffer, F., McCraty, R., & Zerr, C. L. (2014). A healthy heart is not a metronome: an integrative review of the heart's anatomy and heart rate variability. Frontiers in psychology, 5, 1040. https://doi.org/10.3389/fpsyg.2014.01040			X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from BVP signal. Timeseries. Processed with any ML models
HR	Heart Rate, computed as HR=60/IBI.	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from BVP signal. Timeseries. Processed with any ML models
RMSSD	Square root of the mean squared differences between successive RR intervals. Measure of HRV, heart rate variability. Should decrease with stress.	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from BVP signal. Timeseries. Processed with any ML models
NNxx (/ pNNxx)	NNxx=Number of successive RR interval pairs that differ more than xx ms, typically 50ms. pNNxx=NNxx/total number of RR intervals.	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from BVP signal. Timeseries. Processed with any ML models

Metric	Description	Focus Subjects (BE/MW/ MO/CL)	Sub-Domain	Inputs	Reference	Use Cases / Application Scenarios								Spatially Dynamic	Temporally Dynamic	Spatial Resolution	Temporal Resolution	Vulnerable groups	Age	Gender	Self Reporting	Influenced by Experiment	Processing Methodology
						Exp 1 Brain as predictor	Exp 2 Brain as predictor	Exp 3 App	Exp 3 Lab	Exp 4 Outdoor	Exp 5 Clinical	Agent Based Modeling	Policy Making										
VLF, LF, HF	The generalized frequency bands in case of short-term HRV recordings are the very low frequency (VLF, 0–0.04 Hz), low frequency (LF, 0.04–0.15 Hz), and high frequency (HF, 0.15–0.4 Hz). Considering these, typical frequency-domain metrics include VLF, LF, and HF band peak frequencies ([Hz]), its absolute powers ([ms2]; and relative powers [%]).	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from BVP signal. Timeseries. Processed with any ML models
LF/HF	The ratio between LF and HF band powers. Should increase with stress.	MW						X	X	X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Computed from BVP signal. Timeseries. Processed with any ML models
Resp. Rate	Respiration Rate, reflecting arousal. Number of breaths/minute. Should increase with stress.	MW			Iqbal, T., Simpkin, A. J., Roshan, D., Glynn, N., Killilea, J., Walsh, J., Molloy, G., Ganly, S., Ryman, H., Coen, E., Elahi, A., Wijns, W., & Shahzad, A. (2022). Stress Monitoring Using Wearable Sensors: A Pilot Study and Stress-Predict Dataset. Sensors (Basel, Switzerland), 22(21), 8135. https://doi.org/10.3390/s22218135			X	X					Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Estimated from BVP signal. Timeseries. Processed with any ML models
ST	Skin Temperature. Related to certain emotional responses.	MW			Herborn, K. A., Graves, J. L., Jerem, P., Evans, N. P., Nager, R., McCafferty, D. J., & McKeegan, D. E. (2015). Skin temperature reveals the intensity of acute stress. Physiology & behavior, 152(Pt A), 225–230. https://doi.org/10.1016/j.physbeh.2015.09.032			X		X				Yes	Yes	GPS	Seconds	No	No	No	No	Yes	Possible to extract statistical features (avg/ dispersion/ ..). Timeseries. Processed with any ML models
fMRI Activity	ROI activation (contrast)	MW			Heeger, D. J., & Ress, D. (2002). What does fMRI tell us about neuronal activity?. Nature reviews. Neuroscience, 3(2), 142–151. https://doi.org/10.1038/nrn730	x			X					No	Yes	Lab	Seconds	Yes	Yes	No	No	Yes	Timeseries of neural activity of different brain regions, throughout the cognitive task. Processed using a GLM model.
Valence (Starlab EEG feature)	Valence is defined in the pleasure-displeasure continuum, as being more or less positive. It is calculated as result of a Starlab's internal work based in the representation of emotions in a 2D space of valence and arousal.	MW			Müller, M. M., Keil, A., Gruber, T., & Elbert, T. (1999). Processing of affective pictures modulates right-hemispheric gamma band EEG activity. Clinical Neurophysiology, 110(11), 1913-1920. Koelstra, S., Muhl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., … & Patras, I. (2012). Deap: A database for emotion analysis; using physiological signals. Affective Computing, IEEE Transactions on, 3(1), 18-31. Kuppens, P., Tuerlinckx, F., Russell, J.A., Barrett, L.F., 2013. The relation between valence and arousal in subjective experience. Psychol. Bull. 139, 917.				X	X		X		No	Yes		Seconds	No	No	No	No	Yes	Processed from EEG Time-series and spectral power. Computed as percentage of change from a baseline (ERD/ERS%)
Arousal (Starlab EEG feature)	Arousal refers to the general level of alertness and wakefulness of a person. It is calculated as a result of Starlab's internal work based in the representation of emotions in a 2D space of valence and arousal.	MW			Chanel, G., Kronegg, J., Grandjean, D., & Pun, T. (2006). Emotion assessment: Arousal evaluation using EEG's and peripheral physiological signals. In Multimedia content representation, classification and security (pp. 530-537). Springer Berlin Heidelberg. Bos, D. O. (2006). EEG-based emotion recognition. The Influence of Visual and Auditory Stimuli, 1-17. Bos, D. O. (2006). EEG-based emotion recognition. The Influence of Visual and Auditory Stimuli, 1-17.				X	X		X		No	Yes	Lab	Seconds	No	No	No	No	Yes	Processed from EEG Time-series and spectral power. Computed as percentage of change from a baseline (ERD/ERS%)
Cognitive Workload (Starlab EEG feature)	Cognitive Workload is the level of cognitive engagement needed for learning; if it is too high it can negatively affect performance. It is defined as a descriptor that measures the level of cognitive processes from the domain of executive functions. It increases with working memory and level of difficulty of problem-solving tasks.	MW			Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., … & Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. Aviation, space, and environmental medicine, 78(5), B231-B244. Stam CJ, van Cappellen van Walsum AM, Micheloyannis S. Variability of EEG synchronization during a working memory task in healthy subjects. Int J Psychophysiol. 2002 Oct;46(1):53-66. doi: 10.1016/s0167-8760(02)00041-7. PMID: 12374646. Smith, M. E., & Gevins, A. (2005, May). Neurophysiologic monitoring of mental workload and fatigue during operation of a flight simulator. In Biomonitoring for Physiological and Cognitive Performance during Military Operations (Vol. 5797, pp. 116-126). SPIE. Klimesch, W., 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Res. Brain Res. Rev. 29, 169–195.						X			No	Yes	Lab	Seconds	No	No	No	No	Yes	Processed from EEG Time-series and spectral power. Computed as percentage of change from a baseline (ERD/ERS%)
Fatigue (Starlab EEG feature)	Fatigue is defined as a decrease in alertness level that can impair efficiency, performance and memory retrieval.	MW			Jap, B. T., Lal, S., Fischer, P., & Bekiaris, E. (2009). Using EEG spectral components to assess algorithms for detecting fatigue. Expert Systems with Applications, 36(2), 2352–2359. https://doi.org/10.1016/j.eswa.2007.12.043 Lal, S. K. L., & Craig, A. (2001). A critical review of the psychophysiology of driver fatigue. Biological Psychology, 55(3), 173–194.						X												

Metric	Description	Focus Subjects (BE/MW/MO/CL)	Sub-Domain	Inputs	Reference	Use Cases / Application Scenarios Exp 1 Brain as predictor	Exp 2 Brain as predictor	Exp 3 App	Exp 3 Lab	Exp 4 Outdoor	Exp 5 Clinical	Agent Based Modeling	Policy Making	Spatially Dynamic	Temporally Dynamic	Spatial Resolution	Temporal Resolution	Vulnerable groups	Age	Gender	Self Reporting	Influenced by Experiment	Processing Methodology
Attention (Starlab EEG feature)	Attention is defined as a state of focused attentional processing, concentration, persistent focus across time.	MW			Brandmeyer, T., & Delorme, A. (2018). Reduced mind wandering in experienced meditators and associated EEG correlates. Experimental brain research, 236(9), 2519-2528. Anguera, J. A., Brandes-Aitken, A. N., Antovich, A. D., Rolle, C. E., Desai, S. S., & Marco, E. J. (2017). A pilot study to determine the feasibility of enhancing cognitive abilities in children with sensory processing dysfunction. PloS one, 12(4), e0172616. Keller, Arielle S., et al. “Characterizing the Roles of						X			No	Yes	Lab	Seconds	No	No	No	No	Yes	Processed from EEG Time-series and spectral power. Computed as percentage of change from a baseline (ERD/ERS%)
Travel time	By trip, day, person, time in minutes spent travelling. Can be discretized by other variables (e.g. mode)	MO	TRAVEL PERFORMANCE	Trajectory / location data from phone				X		X		X		X	X	Smartphone dependent	Smartphone dependent						Processed from X-ing app
Waiting time	By trip, day, person, time in minutes spent waiting for the vehicle. Ususally relevant for public transport modes. Can be discretized by other variables (e.g. mode)	MO	TRAVEL PERFORMANCE	Trajectory / location data from phone				X				X		X	X	Smartphone dependent	Smartphone dependent						Processed from X-ing app
Activity	Daily activities performed by individuals with time and location data. Can be one of the following categories: work, education, shopping, leisure, personal and escort	MO	DAILY SCHEDULES	Self-reported by the person (the app suggests the activity performed according to the location in subsequent travels to the same place and the person needs to confirm)	Nahmias-Biran, B. H., Han, Y., Bekhor, S., Zhao, F., Zegras, C., & Ben-Akiva, M. (2018). Enriching activity-based models using smartphone-based travel surveys. Transportation Research Record, 2672(42), 280-291.			X				X							X	X	X		Processed from X-ing app
Activity planning	Information on planning and changes related to activities	MO	DAILY SCHEDULES	Individuals report whether the activity performed was planned or not				X											X	X	X		Processed from X-ing app
Mode usage	By trip, day, person. The categories of modes are: car, foot, taxi/transport app, bus, rail, motorcycle, bicycle, scooter, air, other	MO	TRAVEL PERFORMANCE	Trajectory / location data from phone (the individual confirms at the end of the day that has used the mode suggested by the app according to info on route and speed)				X				X			X	Smartphone dependent	Smartphone dependent		X	X	X		Processed from X-ing app
Stop locations	Locations where individuals stopped to perform an activity	MO	TRAVEL PERFORMANCE	Trajectory / location data from phone				X				X		X	X	Smartphone dependent	Smartphone dependent		X	X			Processed from X-ing app
Mobility impairment	Information on whether the person can or cannot walk without the help of other person or a special equipament	MO	TRAVEL PERFORMANCE	Self-reported by the person				X											X		X		Processed from X-ing app
BMI	Body mass index	BE	Physiological data - link the BE	Overweigth and obese patients	Daniel Z. Sui (2003) Musings on the Fat City: Are Obesity and Urban Forms Linked?, Urban Geography, 24:1, 75-84, DOI: 10.2747/0272-3638.24.1.75		x	x	x	x													
Walkability index	Walkability index	BE	PSHYCOPHYSIOLOGICAL DATA - link the BE	Intersection density, slope, land use mix and accomodation density data	Roe J, Mondschein A, Neale C, Barnes L, Boukhechba M and Lopez S (2020) The Urban Built Environment, Walking and Mental Health Outcomes Among Older Adults: A Pilot Study. Front. Public Health 8:575946. doi: 10.3389/fpubh.2020.575946	(x)	x	(x)		x	x												
Slope	topography/slope	BE	PSHYCOPHYSIOLOGI	DEM			x			x													

Metric	Description	Focus Subjects (BE/MW/MO/CL)	Sub-Domain	Inputs	Reference	Use Cases / Application Scenarios Exp 1 Brain as predictor	Exp 2 Brain as predictor	Exp 3 App	Exp 3 Lab	Exp 4 Outdoor	Exp 5 Clinical	Agent Based Modeling	Policy Making	Spatially Dynamic	Temporally Dynamic	Spatial Resolution	Temporal Resolution	Vulnerable groups	Age	Gender	Self Reporting	Influenced by Experiment	Processing Methodology
NDVI	Normalized Difference Vegetation Index - Negative values of NDVI (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Lastly, low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1	BE	PSHYCOPHYSIOLOGICAL DATA - Access to green urban areas	HR and VHR satellite images	https://earthobservatory.nasa.gov/features/MeasuringVegetation and Song H, Lane KJ, Kim H, Kim H, Byun G, Le M, Choi Y, Park CR, Lee JT. Association between Urban Greenness and Depressive Symptoms: Evaluation of Greenness Using Various Indicators. Int J Environ Res Public Health. 2019 Jan 9;16(2):173. doi: 10.3390/ijerph16020173. PMID: 30634488; PMCID: PMC6352234.	x	x	x		x	(x)												
Sq green space per inhb	square meters of green area per inhabitant	BE	PSHYCOPHYSIOLOGICAL DATA - Access to green urban areas	Land use - urban green areas	Sunghee Lee, Youngchul Kim,(2021). A framework of biophilic urbanism for improving climate change adaptability in urban environments,Urban Forestry & Urban Greening, Volume 61, 127104,ISSN 1618-8667, https://doi.org/10.1016/j.ufug.2021.127104.	(x)	x	(x)		x	(x)												
connectivity index	measure of the number of nodes in regard with the edges linking them, accordingly to a planar graph metrics	BE	PSHYCOSOCIAL DATA - related with accessibility and social inclusion	street networks and land use	Chen, Y. R., Hanazato, M., Koga, C., Ide, K., & Kondo, K. (2022). The association between street connectivity and depression among older Japanese adults: the JAGES longitudinal study. Scientific reports, 12(1),	(x)	x	(x)		x	(x)												
floor area ratio	density: a ratio of the building mass to the square footage of the building's lot area	BE	PSHYCOPHYSIOLOGICAL DATA	building and building lot area	Pin Wang, William B. Goggins, Xuyi Zhang, Chao Ren, Kevin Ka-Lun Lau (2020). Association of urban built environment and socioeconomic factors with suicide mortality in high-density cities: A case study of Hong Kong, Science of The Total Environment, Volume 739, ISSN 0048-9697, https://doi.org/10.1016/j.scitotenv.2020.139877.	(x)	x	(x)		x	(x)												
population density	density: a ratio of the number of inhabitants per square area	BE	PSHYCOSOCIAL DATA - related with accessibility and social inclusion	dwellers		(x)	x			x													
Complexity index	Shannon-Wiener index adaption to measure diversity through urban legal activities which means functional diversity	BE	PSHYCOSOCIAL DATA - related with accessibility and social inclusion	street networks and buildings façades	Lorenz, W.E.; Kulcke, M. (2021). Multilayered Complexity Analysis in Architectural Design: Two Measurement Methods Evaluating Self-Similarity and Complexity. Fractal Fractional, 5, 244. https://doi.org/10.3390/fractalfract5040244	(x)	x			x	x												
eveness index	entropy index - measure of "evenness"—the extent to which groups are evenly distributed among organizational units.	BE	PSHYCOSOCIAL DATA - related with accessibility and social inclusion	migrant and ethnicity population	Douglas S. Massey, Nancy A. Denton, The Dimensions of Residential Segregation, Social Forces, Volume 67, Issue 2, December 1988, Pages 281–315, https://doi.org/10.1093/sf/67.2.281		x			x													
sky view factor	Sky View Factor (SVF), defines the ratio of sky hemisphere visible from the ground (not obstructed. by buildings, terrain or trees).	BE /CL	PSHYCOSOCIAL DATA - related with accessibility and social inclusion	buildings height, street width, trees	Fang-Ying Gong, Zhao-Cheng Zeng, Fan Zhang, Xiaojiang Li, Edward Ng, Leslie K. Norford (2018). Mapping sky, tree, and building view factors of street canyons in a high-density urban environment, Building and Environment, Volume 134,ISSN 0360-1323,	x	x			x	x		x						x		x		
UTCI	Universal Thermal Climate Index	CL	Thermal comfort - Heat Exposure	Air temeperatue, Humidity, Mean Radiant Temperature, Wind Speed	Fiala, D., Havenith, G., Bröde, P., Kampmann, B., & Jendritzky, G. (2012). UTCI-Fiala multi-node model of human heat transfer and temperature regulation. International journal of biometeorology, 56, 429-441.					X		X		Yes	Yes	Dependant on input data (meters)	hourly	No	No	No	X	Yes	UTCI source code in python
LCZ	Local Climate Zones	CL	link to the built environment	Data about buuildings, land cover and climate	Stewart, I. D., & Oke, T. R. (2012). Local climate zones for urban temperature studies. Bulletin of the American Meteorological Society, 93(12), 1879-1900.	X	X	X		X		X	X	Yes	Yes	Dependant on input data (km)		No	No	No		No	Wudapt model
Wind Exposure / Wind Comfort		CL	link to the built environment	wind velocities on the pedestrain level	Janssen, W. D., Blocken, B., & van Hooff, T. (2013). Pedestrian wind comfort around buildings: Comparison of wind comfort criteria based on whole-flow field data for a complex case study. Building and Environment, 59, 547-562.					X		X	X	Yes	Yes	Dependant on input data (km)	hourly	No	No	No	X	Yes	Measured or Modeled using CFD programs
UHI	Urban Heat Island Effect	CL	link to the built environment	urban density, urban form, green areas	Oke, T. R. (2010). Urban heat islands. In The Routledge handbook of urban ecology (pp. 144-155). Routledge.					X				Yes	Yes	Dependant on input data (km)	daily average	No	No	No		No	UWG Model
AQ	Air Quality / Air Pollution Exposure	CL	link to the built environment	measured particles	World Health Organization. (2021). WHO global air quality guidelines: particulate matter (PM2. 5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide: executive summary. https://apps.who.int/iris/bitstream/handle/10665/345334/					X				Yes	Yes	Dependant on input data (km)	hourly	Yes	Yes	No		Yes	Measured
Noise Exposure / Pollution	Noise pollution in urban environments	CL	link to the built environment	measures decibel levels	World Health Organization. (2018). Environmental noise guidelines for the European region. World Health Organization. Regional Office for Europe. https://www.euro.who.int/__data/assets/pdf_file/0008/383921/noise-guidelines-eng.pdf					X				Yes	Yes	Dependant on input data (meters)		Yes	Yes	No		Yes	Measured

*e*MOTIONAL Cities
Mapping the cities through the senses of those who make them