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Horizon 2020

Societal Challenge: Improving the air quality and reducing the carbon footprint of European cities

Project: 690105 – ICARUS

Full project title:

Integrated Climate forcing and Air pollution Reduction in Urban Systems

D1.3 - The use of sensor technologies in defining external exposure at individual level (Methodological review)

WP1 Methodological framework development

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TABLE OF CONTENTS

Contents

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1 Introduction

One of the foreseen activities regarding population exposure and health impact assessment in ICARUS participating cities is also collection of multi-sensor data for personal exposure monitoring. This will be achieved by the use of new sensor technologies available nowadays. Namely, in recent years progress in development of various wireless devices, smartphone applications and especially downsizing of monitoring technologies and costs, enabled environmental stressors and exposure factors to be measured more easily and frequently, thus providing a more reliable “time–geography of exposure” shifting the current paradigm from a population to an individual level. However, given the fact that market is flooded with various types of such devices, the selection process as well as setting the criteria for their selection are not always straightforward.

To this end, the aim of this document is to review the state-of-the-art in the field of external sensor technologies and geo-referenced systems used to define the external exposure at individual level, and in this way directly support the process of selection of suitable candidate sensor technologies to be used by volunteers within WP4 of the ICARUS project (*Task 4.1 Collection of multi-sensor data for personal exposure monitoring*).

The review was conducted in two steps considering specifics of ICARUS goals and demands. As a first step, scientific literature reporting applications of personal air quality sensors and personal activity sensors for the determination of personal exposure was reviewed. The literature review has been made following the Extensive Literature Search (ELS) principles and guidance. Within this initial step, the review was focused, but not limited, to provide answers to two general questions. First, to what extent new sensor technologies are being used in practice to assess exposure of individuals; and second what kind of information these technologies provide in terms of complexity, level of detail, and integration with other tools and approaches used for the assessment of the exposure.

As fitness for specific purpose highly depends on characteristics and capabilities of individual sensor, in the second step, the review was extended to include information on sensor technical characteristics and performance. For this purpose, in addition to reviewed scientific literature, new information sources including related previous and ongoing EU projects, evaluations performed by sensor manufacturers as well as independent ones were investigated. Technical specifications of sensors that influence their usefulness and trustworthiness and the outcomes of performance evaluations were then summarised in a structured way. During this second step of the review, the focus was on the following characteristics of the sensors: portability/wearability, user-friendliness, cost, data capturing and transfer protocols, and validity/reliability of data collected.

2 Application of sensors for personal exposure assessment

Review of scientific literature reporting applications of personal air quality and personal activity sensors for the determination of personal exposure has been made following the Extensive Literature Search (ELS) principles and guidance, i.e. an approach that allows transparency and reproducibility of the outcomes. Details of the approach are given in the previously prepared protocol (Kocman et al., 2016), and are summarized here, as follows. The systematic reviews were conducted according to the following main steps (EFSA, 2010):

- *Search* which entails an extensive and sensitive review of several data sources performed in order to retrieve as many studies as possible, fitting the eligibility criteria;
- *Selection* which consisted of two consecutive steps: i) a first screening of the information contained in titles and abstracts, and ii) a selection based on full-text reports;
- *Data collection* aiming at getting this information, which answers previously defined research questions;
- *Quality assessment/control,* which covers the design, execution, analysis and outcomes of an ELS, and
- *Data synthesis and reporting* through which the large amount of information collected was clearly structured to make their interpretation transparent, consistent, and auditable.

2.1 Study inclusion/exclusion criteria

The review focuses on sensor technologies that can be used for defining external exposure at individual level. Therefore, the emphasis was on portable/mobile/wearable devices for personal use. Following the definition of Loh et al. (2014), "*personal sensor technologies*" are small-scale, relatively low-cost devices that can record or wirelessly send data to a computer, smartphone or tablet. In this review, we only consider studies dealing with devices that meet these criteria in relation to exposure assessment.

In broader terms, we distinguish between two types of sensors: air quality sensors (AQ), and physical activity (PA) including location (GPS) tracking sensors. Within the first group we consider sensors measuring presence/concentrations of gases, particulate matter as well as specific environmental (e.g., meteorological) parameters. Second group comprise various physical activity sensors: accelerometers, respiration, heart rate, R-R interval, breathing rate, etc.

2.2 Methodology of study collection

Decisions on study selection were made in two stages. First, based on screening of titles and abstracts for relevance to the study question by working group/reviewers. For studies that passed first screening or for those that clear decision could not be made, examination of full-text for eligibility followed. The review and selection was done by at least two reviewers.

In the first screening phase all studies reporting the use of any kind of personal sensors designed for determination of personal exposure were considered. We limited our review to studies reporting applications of these devices rather than their development. This characteristic of a study served as a first general inclusion/exclusion criterion. In the second phase, following the full-text evaluation, studies reporting the use of personal sensors in a transparent and verifiable way, clearly describing methods of calculation/approach used to assess exposure, were considered.

2.2.1 Data sources, search methods and data collection

Published peer-reviewed literature was searched using three database platforms: Web of Science, SCOPUS and PubMed. The review covered two groups, based on the two groups of sensors as defined above, using the search terms and Boolean operators as given below. Additional studies and their sources were checked based on the references in the literature considered. The outcome of the overall search was then summarized following the approach and example provided by Jensen (2016).

Search method

Air quality sensors

Search terms and Boolean operators (strings): [“mobile sensor” OR “personal sensor” OR “micro sensing unit”] AND [“air quality”] AND [“exposure” OR “health”]

The searches in Web of Science resulted in 71 hits, searches in SCOPUS in 128, and searches in PubMed in 10. Out of total 209 hits, 55 were duplicates. Therefore, in total 154 studies/papers were considered for first screening (shown in Appendix A).

Physical activity sensors

Search terms and Boolean operators (strings): [“mobile sensor” OR “personal sensor” OR “micro sensing unit”] AND [“personal movement” OR “personal activity” OR “personal intensity” OR “GPS” “accelerometer” OR “heart rate” OR “breathing” OR “respiration” OR “R-R interval”] AND [“exposure”]

The searches in Web of Science resulted in 72 hits, searches in SCOPUS in 112, and searches in PubMed in 21. Out of total 205 hits, 66 were duplicates. Therefore, in total 139 studies/papers were considered for first screening (shown in Appendix B).

Study selection and data collection

During initial selection the following information was extracted from individual studies based on title and abstract screening: first authors last name, year of publication, journal name, type of paper (PAP-paper, PRO-conference proceeding, REW-review, BOOK-book or book chapter), and whether or not title/abstract indicate sensors were in use/applied (YES - any kind of use of sensors in real-life conditions, NO – no indication of reported application of sensor technologies described in the study).

Only studies that passed the application criteria at title and abstract screening stage have been selected for the full-text screening. During second screening stage the following information was extracted from individual studies: Indoor and/or outdoor sensors use, type of users/population involved in the study including their number, location, list of parameters measured by sensors, data visualization type, exposure assessment method used in the study, and main outcomes of individual study.

In the process of full paper reading, studies which did not meet general criteria – i.e. relation to external exposure at individual level- were excluded. Also studies which passed the screening at the title and abstract stage and for which full text was not available/accessible, and therefore could not have been thoroughly examined, were excluded from further review.

2.2.2 Reflection to search method and its outcome

Table 1 shows a flow chart of literature search on Air Quality sensors: the total number of references retrieved after removal of duplicates and exclusion in the initial screening and after reading full paper, respectively. Following the procedure outlined in Table 1, in total 37 references (including 7 additional from references) were included for analyses. 84 studies excluded during initial screening are those where use/application of portable/mobile/wearable AQ devices is not mentioned in the title or abstract. Papers excluded in the second phase (40) comprise of those where reading of full paper revealed a discussion that is limited to wireless architecture testing, data-flows, static AQ monitoring, modelling or similar without actual application involving users and studies where full paper could not be accessed.

Table 1: Flow chart showing how Air Quality sensors studies were included or excluded

<table>
<tr><th colspan="4">Literature search on Air Quality sensors</th></tr>
<tr><td>Web of Science

71</td><td>SCOPUS

128</td><td>PubMed

10</td><td>Add. from ref.

7</td></tr>
<tr><td colspan="4">Total

216</td></tr>
<tr><td rowspan="2">Included

37</td><td colspan="2">Excluded

124</td><td rowspan="2">Duplicates

55</td></tr>
<tr><td>Excluded during initial screening

84</td><td>Excluded after reading full paper

40</td></tr>
</table>

Table 2 shows a flow chart of literature search on Personal Activity sensors: the total number of references retrieved after removal of duplicates and exclusion in the initial screening and after reading full paper, respectively. Following the procedure outlined in Table 2, in total 19 references were included for analysis. Similar as in the case of AQ sensors, studies excluded during initial screening are those where use/application of portable/mobile/wearable sensors is not mentioned in the title or abstract, and papers excluded in the second phase comprise of those where reading of full paper revealed a discussion that is not relevant for this ELS.

Out of all studies included for analysis from both searches, some were evaluated within both groups. Therefore, the final outcome of ELS (combined AQ and PA references) is 48 studies.

Table 2: Flow chart showing how Physical Activity sensors studies were included or excluded

<table>
<tr><th colspan="4">Literature search on Physical Activity sensors</th></tr>
<tr><td>Web of Science
72</td><td colspan="2">SCOPUS
112</td><td>PubMed
21</td></tr>
<tr><td colspan="4">Total
205</td></tr>
<tr><td colspan="4"></td></tr>
<tr><td rowspan="2">Included
21</td><td colspan="2">Excluded
118</td><td rowspan="2">Duplicates
66</td></tr>
<tr><td>Excluded during initial screening
90</td><td>Excluded after reading full paper
28</td></tr>
</table>

Initial title and abstract screening revealed that a vast majority of hits using the above mentioned search terms and Boolean operators resulted in studies dealing with issues such as sensors development, testing and validation, data processing and visualization, development of data-flow architectures, static monitoring and modelling rather than the use of sensor technologies in defining external exposure at individual level. Moreover, although exposure is explicitly mentioned in most of the studies, the above findings remain also after full text reading, i.e. after the second review stage.

Within the AQ sensor search “health” was also used as a search term in addition to exposure, as an “extension” for exposure assessment; we observed during the initial screening many authors use term “health” in connection to exposure in broader terms (e.g. as a health risk, health impact, environmental health etc.). The intention was to include as many studies relevant for this ELS as possible. However, analyses of the search outcomes releveled that inclusion of this search term did not result in increased number of relevant studies. Therefore, “health” was omitted as a search term in case of physical activity sensors.

The quality control of the search method included reviewing and studies selection by two independent reviewers (independence means that they performed reviews without mutual consultation). In case of disagreement, study was selected for full text reading. Additional studies obtained from references of the initially checked literature are those that are dealing with the use of personal senor technologies, however were not included in the first list of hits (using the search protocol), since mobile or personal sensors are not mentioned in their title or abstract.

Both searches (AQ and physical activity) resulted in numerous hits where both types of sensors are discussed. For this reason, in the following sections discussion on both group of sensors is combined.

2.3 Findings

2.3.1 Characteristics of studies included in ELS

Type of paper

Out of 48 studies 37 are scientific articles (including review papers), and 11 are conference papers. Although no time restrictions were applied during search, only one study dates back to 2000, while all others are studies published after 2009, suggesting that this topic is a rather new one. Majority of included studies are focusing on outdoor environment or both indoor and outdoor, with only 4 studies being indoor specific.

Parameters measured

AQ parameters that were investigated in selected studies are: CO, O3, CO2, PM, VOC, NOx, HCHO, and CH4. In Figure 1, summary of AQ parameters and their frequency in included studies is given. Particulate matter (measured either as PM10, PM2.5, UFP or black carbon) is the most often measured parameter, followed by nitrogen oxides (either NO_2, NO or NO_x), carbon monoxide and ozone.

Tracking of activity patterns used in included studies comprise various approaches; from recall-based time-microenvironment-activity budget diaries filled by participants without using any sensors, to more sophisticated measurements of acceleration, heart rate, cadence, nasal airflow etc. Within the studies included in ELS, use of various motion sensors and heart rate measurements are the most common approaches.

Combination of AQ and physical activity data/information

Apart from basic GPS location measured either by the device itself or by the accompanying smartphone, and by which activity patterns of an individual can be estimated, in approximately half of the studies AQ measurements are combined with various types of physical activity tracking of the individual.

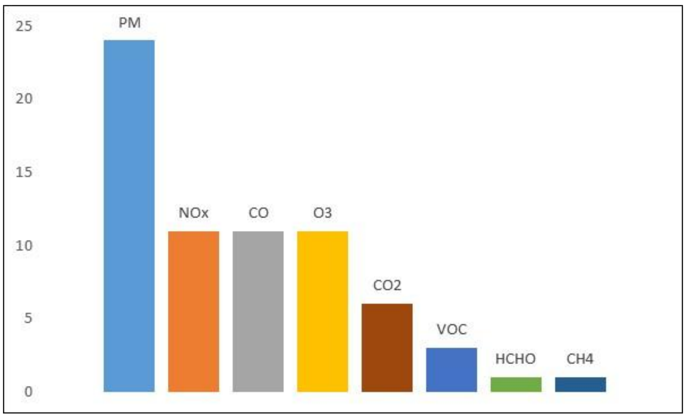


Figure 1: Frequency of AQ parameters measured in included studies

Spatial distribution of studies

A vast majority of selected studies were conducted in urban settlements of Europe, the rest being distributed in Asia, Australia and USA (Figure 2). For quite a few studies, authors do not report exact location. Spatial distribution of study locations indicates the prevailing use of new sensor technologies in high income countries. As noted by Nieuwenhuijsen (2016), these are countries where people have smartphones supporting use of Apps needed to characterize exposure.

Figure 2: Distribution of studies included in ELS with reported location

Population groups/users

Selected studies cover a wide range of population groups/users involved, both in terms of their type and number: volunteers, students, hospital workers, mail carriers, bikers etc. A general observation is that most studies do not report details on user recruitment procedures or the rationale for their selection, and often refer to them simply as "volunteers", "local population", "users", "people", "subjects" or similar. Often information on number of people and spatiotemporal extent of the study is missing.

Data visualization, processing and access

Type of visualization of signals measured by sensors in selected studies can be broadly classified in following three groups in increasing order of complexity: (i) simple graphic plots; (ii) time and space coverage of concentrations measured on a geo-referenced maps, and (iii) various forms of processed data/information (e.g. representation in a form of air quality index, clusters, heat maps or other aggregated form). There are various approaches and levels of data retrieval and access. For some sensors users can access data previously collected retrospectively only. Often sensing devices communicate with a smartphone where data can be visualized and accessed through mobile application interface. In this later case user can access personalized information in a real-time.

2.3.2 Assessment of selected studies

Related review papers

In the following section a summary of the main outcomes of the four review papers included in this ELS is given, focusing on what findings authors of these reviews report in relation to the use of sensor technologies in defining external exposure at individual level.

Steinle et al. (2013) reviewed assessments of human exposure to air pollution and concluded that individual exposure estimates derived from real-time personal pollution monitors are inherently different from approaches using aggregated data, due to the higher spatial and temporal resolution in contrast to fixed site or stationary indoor monitors. They recognise availability of low-power, high sensitivity sensors for priority air pollutants as a limiting factor for the development of small, real-time mobile devices (Steinle et al., 2013).

Borrego et al. (2015) reviewed the role of monitoring and modelling techniques in the light of challenges for the air quality directive, and concluded the following: The utilisation of AQ micro-sensors is still not mentioned for regulatory purposes in European legislation, nevertheless their use can be particularly valuable to have highly spatially and temporally resolved air quality data and to improve exposure assessment. Low-cost sensing technologies sensors are extremely new, and much research remains to be done to integrate these technologies. Special emphasis should be given to the quality check of the sensors performance against conventional methods, as well as, for the study of the combined effect of low cost technologies with conventional methods.

Within the survey of wireless sensor network based air pollution monitoring systems, Yi et al. (2015) discuss advantages and disadvantages of what they call Community Sensor Networks (CSNs) – sensor nodes carried by the users. They recognise the following advantages of CSNs: cost efficiency, availability of personal air pollution information, public-driven property, automatic gathering property, mobility of sensors and public behaviours acquisition ability. According to Yi et al. (2015), limitations of CSNs are: low data accuracy and reliability, privacy issues, badly calibrated and maintained sensors, serious constraint on energy consumption, uncontrolled or semi-controlled mobility, 2-dimensional data acquisition, and serious limitations on weight and size.

Nieuwenhuijsen (2016) discusses the use of smartphones, GPS devices and small sensors to measure environmental exposures in the context of urban and transport planning; and recognises these as important new research tools that can provide decision-makers not only better data on the complexity of factors in environmental and developmental processes affecting human health, but also enhanced understanding of the linkages.

Loh et al. (2017) discussed the possibilities and laid out several criteria for using smart technologies for external exposome studies as well as their limitations and challenges. The authors pointed out that at this time sensors are best suited for assessing location and activities, which are key influencing factors for all three spheres in the exposome (i.e. general external, specific external and internal exposure) and that currently sensors are less well suited to reliably measure actual hazards, such as air pollution or noise. Unlike conventional forms of exposure assessment one advantage of data gathering from smartphones and sensor-based technologies is that information from different wireless devices and apps can be gathered in the field and stored with less need for researcher intervention. A key question that needs to be addressed is what is the overall uncertainty introduced by the use of ubiquitous personal sensors, versus the uncertainty resulting from the temporally and spatially deficient regulatory monitoring networks. Moreover, issues of data ownership and data protection need to be carefully taken into account to allow ubiquitous environmental health monitoring to become an everyday reality. Harmonization of data handling and standardization of data privacy and confidentiality procedures are needed to support the wider use of personal sensors in this context. The authors concluded that there are still challenges for sensing devices in terms of data quality, form and function, cost, management, and analysis of the amount of data that could potentially be collected. To this end a practical approach currently suggested is to document spatial time–activity profiles of subjects, and to integrate these data with other existing datasets, such as air and water quality, to generate modelled estimates of a person's external exposome

Sarigiannis and Gotti (2014) reviewed the more recent technologies developed in the frame of scientific research projects or available on the market to reduce exposure measurement error through the use of by various type of sensors which allow shifting the current paradigm of exposure assessment from a population to an individual level. The authors examined the main limitations and challenges the scientific community needs to face to fully benefit from the unprecedented amount of "individualized exposure data" (Big Data) which indeed requires statistical advances, sophisticated data mining techniques, computing power as well as a careful sharing of data sources while also maintaining privacy protections for personal data. A further challenge regards data quality assurance. In this regard the key challenge is that sensors, especially commercial ones, need to balance optimally accuracy and reliability against cost. The authors concluded that there still is the need to develop portable monitors that can measure multiple pollutants and that it would be desirable to reduce the size of such sensors so that people and especially children can carry them more easily.

Levels of exposure assessment

Overall, analyses of included studies revealed a variety of approaches with different levels of complexity in exposure assessment at individual levels. For the use of AQ sensors, these approaches can be classified into three groups as schematically shown in Figure 3. At its most basic level, exposure assessment is limited to providing users with personalized AQ information only. In this way, people can track AQ levels at their routes, identify the most critical areas in their living environment in terms of air pollution, and characterise patterns of exposure with very detailed spatial and temporal resolution. This is the most common approach in studies included in ELS. Within second general group, personalized georeferenced AQ information is combined with the physical activity profile of the individual. This approach allows examination of an individual's estimated exposure through space and time, which may provide new insights into exposure–activity relationships not possible with traditional exposure assessment techniques (Adams et al., 2009). Based on the combined information personal intake can then be calculated. In the third group there are studies that combine measured air concentrations and physical activity data with additional external information or services, e.g. modelled AQ values, on-line health information services and similar applications.

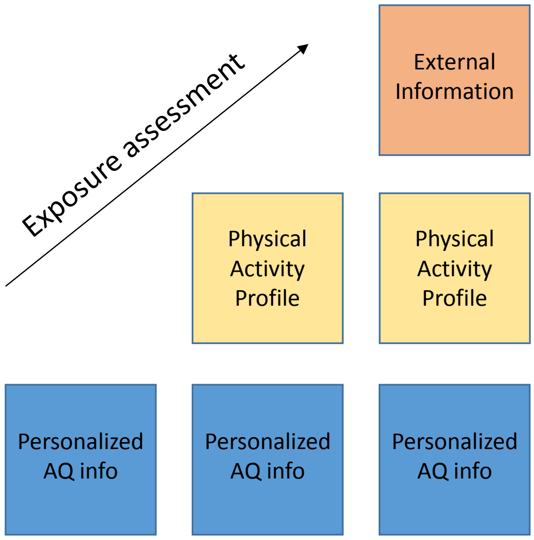


Figure 3: Various approaches and complexity of external exposure assessment at individual level

Personalized spatiotemporal information

Within this group, many studies confirmed very high spatiotemporal variations of air pollutants in urban environments, and consequently the need for incorporating this information into personal exposure assessment. Chen et al. (2012) demonstrated variation in exposure to VOC under various circumstances; higher exposure in high traffic outdoor areas, inside renewed rooms or near chemical emitting products, and in man-made disasters. Black et al. (2012) confirmed strong diurnal variations in human exposure to ozone using portable ozone sensors. Similar, Delgado-Saborit (2012) identified peak exposures to black carbon and NO_2 in daily routine by portable sensors as well as which activities contributed the most to these peaks, such as cooking and commuting. Using CO measurements as a surrogate for benzene, portable CO sensors were used to quantify information on exposure of the residents of Trento to benzene with a detail no reachable through conventional approaches and suitable for an enhanced activity of decision makers (Dalla Valle et al., 2017). Using data aggregation techniques based on measurements of PM, NO_x and O_3, very distinct air quality clusters were identified in Edinburgh (Arvind et al., 2016). A vast majority of studies included in ELS took place in urban environments where traffic related PM is usually considered as most problematic exposure pathways. Consequently, there is a substantial amount of literature addressing this problem with the use of new sensor technologies and which are all reporting very large spatiotemporal variability of various PM forms, and consequently emphasizing the need for very high-resolution data for exposure assessment (e.g. Nyhan et al., 2014; Snik et al., 2014; Zwack et al., 2012; Boogaard et al., 2009; Thai et al., 2008; Dons et al., 2011).

Combining air pollution data with human activity using wearable sensors

The measurement of highly-resolved, temporospatially-referenced exposure data allows for rigorous exposure assessment of mobile cohorts in the workforce or community (Adams et al., 2009). At its most basic level, physical activity patterns are tracked using time-activity diaries. Using this approach, volunteers are asked to take notes during the day and report their activities either on paper or online into a web form (e.g. Buonanno et al., 2014; Gall et al., 2014; Steinle et al., 2015; Lu et al., 2015). For example, based on a recall-based time-microenvironment-activity budget diary combined with continuous CO_2 measurements, Gall et al. (2014) concluded that majority of exposure levels of possible concern occurred in the home, followed by work, transit and other indoor locations. Time-activity diaries are combined with the use of various commercially available portable positioning system receivers, usually GPS-enabled smartphones that give information about spatiotemporal movements of people involved in studies. In this rather simple way, very high frequency and resolution of spatiotemporal data can be obtain and the main challenge is appropriate treatment of these large amounts of data. Adams et al. (2009) apportioned spatial data into predetermined location–activity categories (work/school, home, transit) with a simple, temporospatially-based algorithm and combined this information with PM levels measured. Similarly, Steinle et al. (2015) used contextual and time-based activity data to define six microenvironments (MEs) to assess everyday exposure of individuals to short-term PM2.5 concentrations. They conclude that due to the substantial variability across and between MEs, it is essential to measure near complete exposure pathways to allow for a comprehensive assessment of the exposure risk a person encounters on a daily basis (Steinle et al., 2015). Another is example of Wu et al. (2012) who used modelled PB-PAH (particle-bound polycyclic aromatic hydrocarbon) values to classify major time-activity patterns (indoor, in-vehicle, and other) based on the raw GPS data. They developed multiple-linear regression and mixed effect models to estimate averaged daily and subject-level PB-PAH exposures and concluded that time in vehicle was the most important determinant of personal PB-PAH exposure (Wu et al., 2012). Along these lines, Ryan et al. (2015) demonstrated high spatio-temporal variability of ultrafine particles (UFP) and increased exposure during transit to and from school. In addition to GPS tracking and microenvironment characterisation, there are other devices used to determine physical activity of an individual, however to a much lower extent. For example, Seto et al. (2009) used custom-built motion sensor board that includes measurements from a triaxial accelerometer and a biaxial gyroscope to monitor physical activity. Rodes et al. (2003) tested triaxial accelerometers and found a strong linear correlations with participant's ventilation volumes. Using phone's triaxial accelerometer, de Nazzele et al. (2013) combined modeled urban air pollution concentrations and data from the literature to estimate exposure and inhalation of urban air pollution accounting for the daily activities. Heart rate is another physical activity proxy used in studies. Hu et al. (2014a) calculated intake of CO based on data from participatory systems and individual's on-body activity monitor measuring heart rate calculated to respiratory minute volume. They showed that the individual's activity, such as jogging, cycling, or driving, impacts their intake, and also developed an app that gives them this personalised information (Hu et al. 2014a). Hart rate was also one of the parameters included in a personal sensor set by Nieuwenhuijsen et al. (2014) to continuously measure personal exposures and to assess part of the current exposome and acute health responses. Hu et al. (2014b) used human energy expenditure data to give individuals real-time personal air pollution exposure estimates. They used algorithm to convert energy expenditure rate to intake, and demonstrated that intake due to inhalation might be significantly higher while doing fitness activities, even under lower air pollution levels, though driving and walking do also contribute to the whole day's dosage. Huck et al. (2017) combined measurements of nasal airflow, NO_2, and location (GPS) to assess personal exposure to traffic pollution, as a function of the concentration of pollutants in the air and the frequency and volume of that air which enters lungs. In their case exposure is predicated upon the simple equation combining concentrations and airflow and assumption that doubling either the pollutant concentration, the airflow depth or the airflow rate would double exposure calculation returns a value on a relative index scale of 0 (no exposure) to 1 (highest exposure) (Huck et al., 2017).

Exposure assessment combined with external information

Yang et al. (2016) upgraded the AQ-physical activity approach to assess exposure of an individual by combining objective data (PM, hearth rate and cadence measurements) with subjective data using questionnaires to record participants perception of air quality, as well as reported health symptoms.

Zeiger and Huber (2014) demonstrated a platform that combines participatory sensing of number of AQ parameters with online health information service that generates a heat map, identifies hotspots, provides recommendations and calculate routes with the lowest air pollution exposure. Similarly, Seto et al. (2009) integrated monitoring of a child's activities, geographic location, and exposures to PM with an online information service providing various modules for asthma patients. Along these lines, Hedgecock et al. (2010) developed a web-based platform where high resolution AQ data from both mobile and static sensors are combined with an interface that offers users various applications to promote health and pollution awareness, including a green trip planner, whereby users can plot routes between two locations based on a path of least exposure to specific pollutants, and an exposure estimator, which allows users to calculate previous levels of exposure to harmful pollutants based only on a single timed GPS track. In this latter case, exposure estimator App gives to the user a list of times when the user experienced pollution levels over a self-defined threshold level, or average concentration levels over specified time ranges (Hedgecock et al., 2010). Pilla et al. (2015) combined results obtained by portable PM monitor with a GIS model for personal exposure to PM10. Their GIS model is validated by modelling the personal exposure to particulate matter of commuters travelling to and from work using different routes and different transport modes (Pilla et al., 2015). Predić et al. (2013) built a mobile participatory sensing infrastructure that utilizes smartphone accelerometer for activity detection, external air quality data, and USB pluggable O_3 sensor. They used these heterogeneous data to estimate people's daily pollutant exposure. They scaled exposure intensity based on activity type, burned calories and movement speed, using metabolic equivalents of various activities tables. User's location with classified activity was then matched against air quality interpolated values and exposure is calculated with multiplication factor taken into account (Predić et al., 2013).

2.3.3 Fitness for purpose

Most of the studies included in ELS do not provide much details on sensors performance, quality assurance and controls. However, it is recognized in the scientific community that data accuracy and reliability when using portable sensing devices might be a problem, as sensors are used in a wide range of environmental conditions and setups. It is known that due to the complexity of atmospheric environment and interaction between various gases, in real time applications sensors might suffer from reduced sensitivity, specificity and stability (Lewis and Edwards, 2015). Moreover, their performance might be highly affected by variation in speed and sensor placement with respect to direction of movement during use (Lerner et al., 2015). For all these reasons, scientists like Lewis and Edwards (2015) recommended for caution when using new sensor technologies. According to them, an agreement should be made on what degree of sensor accuracy is acceptable before the actual use, and their fitness for purpose should be demonstrated.

With this in mind and considering specific objectives of ICARUS, in the following sections the review was extended to the overview of sensors technical characteristics and their performance.

3 Review of sensor technologies

In this section a review of sensor technologies available nowadays that can be used for defining external exposure at individual level is given. For this purpose, in addition to reviewed scientific literature, new information sources including related previous and ongoing EU projects (summarised in Appendix C), sensor producer's web pages and evaluation reports performed by either sensor manufacturers or independent ones were investigated.

3.1 Sensors characteristics

Considering specific objectives of the ICARUS - collection of multi-sensor data for personal exposure monitoring – review of available low-cost sensor technologies designed for both air quality and personal activity monitoring focused on the following technical specifications and characteristics specified in this section. Based on these specifications/characteristics selection of suitable candidate sensor technologies to be used by ICARUS volunteers will be made (MS9).

<u>Air quality sensors:</u>

Parameters measured – whether one or a combination of different air pollutants can be measured by a single device; availability of additional parameters such temperature and relative humidity that can influence AQ sensors performance and help during interpretation/post-processing of signals from low-cost sensors.

Portability – whether monitoring device is designed for personal exposure to be monitored explicitly, either carried or worn by a person during their regular daily routine or placed as a static device in indoor environments.

User-friendliness - this is important parameter determining whether a non-scientifically trained individuals will be willing and able to use the device; it depends on its design (size/shape/weight/power supply…) and especially ease of use. The latter depends on effort one has to put to operate with the device. For example, a bulky setup, especially in the case of multi-sensor approach, and complicated usage for non-technical people, can make user unwilling to participate and use these devices in everyday life.

Low-cost – parameter enabling widespread deployment considering number of participating cities and total number of volunteers recruited in the project.

Data collection and transfer protocols – ability to collect, store and transmit high-resolution data; connectivity with internet and remote accessibility of data; availability of smartphone applications and web portals that support community based monitoring.

Validity/reliability of data collected – whether performance of the sensor was evaluated and reported.

<u>Personal activity sensors:</u>

For the personal activity sensor capability to monitor the following parameters was investigated: Steps, Active minutes, Calories/Energy, Sleep, Respiration, Heart Rate, Oximetry, GPS, Temperature, Light.

3.2 Specifications of low-cost sensors

3.2.1 AQ sensors

In this section summary of characteristics for various AQ sensors is given. Considering the purpose and technological development of individual sensor, both low-cost devices for monitoring of particulate matter and those for monitoring of gaseous pollutants can be classified in different groups.

In terms of portability, AQ sensors can be divided among stationary and portable ones. In the context of ICARUS needs and exposure assessment at individual level, stationary ones are designed for the indoor use, while among the portable ones there is a sub-group of wearable sensors, defined here as sensors that are specifically designed to be worn by a person during their regular daily routine for longer period of time (hours).

In terms of technological development, we adopt here the definitions of Rai et al. (2017) and distinguish between so-called *ready-to-use modules* and the *stand-alone sensors*. Within the first group there are modules (also referred in literature as sensor nodes, kits, units or packages) with their own data acquisition, storage, and display system, while stand-alone sensors for proper functioning require integration into an appropriate data acquisition and storage system.

In the following tables, characteristics of individual sensors are systematically summarised. For each of the sensors reviewed, information on general features (size, weight and power supply), cost, data acquisition and transfer protocol, portability, working environmental conditions as well as information of their performance evaluation is given.

Information on the performance evaluation comprise a summary of various testing and specifications supplied by sensor manufacturers as well as from independent evaluations. In this part emphasis was on field evaluations (e.g. co-locations with reference instruments), as it is known that co-location calibrations perform better than laboratory calibrations, as these latter suffer from bias and difficulty in covering the necessary parameter space (Piedrahita et al., 2014). Among sensors specifications summarised for individual sensors, results of various evaluations performed either by sensor manufacturers or independently are given. This includes various parameters reported as part of the quality control. Adopting definitions of Air Quality Sensor Performance Evaluation Center (AQ-SPEC, 2017) one or more of the following parameters are usually reported:

(i) *Linearity* reported as correlation (R^2) between co-located sensor and reference instrument;

(ii) *Accuracy* given as degree of closeness of sensor concentration measurements to the actual concentration value measured using reference instruments;

(iii) *Precision* given as a variation around the mean of repeated measurements;

(iv) *Response time* given as time needed for sensor to respond to changing conditions;

(v) *Interference of co-pollutants* defined by a pollutant other than the one being measured; and

(vi) *Temperature (T) and relative humidity (RH) influences* caused by variations in ambient T and RH.

Ready-to-use modules

Wearable sensors

Sensor model	Airbeam		
Air pollutants	PM2.5		
Add. param.	T, RH, GPS		
Size (cm):	10.5x10x4.6	*Data protocol:*	Bluetooth, phone app
Weight (g):	200	*Portability:*	wearable
Power supply:	3.7V Li-battery	*T range (˚C):*	
Cost ($):	250	*RH range (%):*	
Performance evaluation	Specifications by manufacturers: - Particle Sensor: Shinyei PPD60PV, concentration range: up to 400 $\mu g/m^3$ - comparison with pDR-1500 instrument: R^2=0.98 for values <24 $\mu g/m^3$, R^2>0.94 for values <100 $\mu g/m^3$, nonlinearity above 100 $\mu g/m^3$ Independent evaluations: - r=0.65-0.66 versus MetOne BAM 1020 FEM PM2.5 monitor (Jiao et al., 2016)		

Sensor model	TZOA		
Air pollutants	PM2.5 and PM10		
Add. param.	T, RH, pressure, UV, ambient light		
Size (cm):		*Data protocol:*	USB, SD, Bluetooth, smartphone app
Weight (g):		*Portability:*	wearable
Power supply:	Micro-USB	*T range (˚C):*	
Cost ($):	Upon request	*RH range (%):*	
Performance evaluation	Specifications by manufacturer: - TZOA-Consumer and TZOA-Research versions available, the latter designed for more rugged environments and for longer measurement campaigns - Interacts with TZOA App - Crowdsourced maps - R^2=0.89 versus DustTrack monitor (0.4 mg/m^3 loading)		

Sensor model	RTI MicroPEM		
Air pollutants	PM2.5, PM10		
Add. param.	accelerometer data		
Size (cm):		*Data protocol:*	WI-FI
Weight (g):	<240g	*Portability:*	wearable
Power supply:	3 AA batteries	*T range (˚C):*	-10 - 35
Cost ($):	2.000	*RH range (%):*	<90
Performance evaluation	Specifications by manufacturers: - Particles are detected using a nephelometer, concentration data at 1-second intervals - dynamic range of 1 mg/m^3 to 10,000 mg/m^3, accuracy >90%, precision >90% Independent evaluations: - R^2 = 0.64-0.84 versus Grimm Model EDM180 PM2.5 monitor, no T effect, no RH effect <90% (Williams et al., 2014a)		

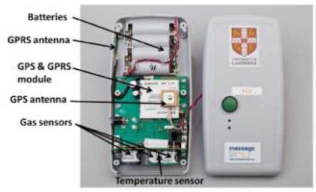
Sensor model	CairClip		
Air pollutants	NO_2, O_3, H2S and sulphur compounds, NH3		
Add. param.			
Size (cm):	3.2x6.2	*Data protocol:*	USB, UART
Weight (g):	55	*Portability:*	Wearable
Power supply:	recharge. batt.	*T range (˚C):*	-20 – 40
Cost ($):	Upon request	*RH range (%):*	10 - 90
Performance evaluation	Specifications by manufacturers: - LOD: 20 ppb, Concentration range: 0-250 ppb (http://cairpol.com/wp-content/uploads/2017/05/Cairsens-O3NO2-0-250ppb-Technical-specifications.pdf) Independent evaluations: - Ozone: r=0.82 - 0.94 vs. Thermo Fisher Scientific FEM 49I O3 monitor (Jiao et al., 216) - NO_2: r=0.42 - 0.76 vs. Thermo Fisher Scientific FEM 42C NO2 monitor(Jiao et al., 216) - Ozone: Excellent linearity over the full operating (R^2>0.99), LOD: ≤11 ppb, excellent precision observed under both high and low challenge conditions (≤4 ppb), laboratory experiment (Williams et al, 2014b).		

Sensor model	Everyaware SensorBox		
Air pollutants	CO, NO_2, O_3, VOC		
Add. param.	T, RH		
Size (cm):		*Data protocol:*	Bluetooth, phone app
Weight (g):		*Portability:*	wearable
Power supply:	Mini USB	*T range (˚C):*	-30-85
Cost ($):	research	*RH range (%):*	5-95
Performance evaluation	Specifications by manufacturers: - components: Alphasense CO-BF, CO sensor; E2V MiCS-5521, CO sensor, and MiCS-2710, NO_2 sensor; Figaro 2201, gasoline and diesel sensor; E2V MiCS-2610, Ozone sensor; Applied Sensors AS-MLV, VOC sensor - communication with AirProbe mobile application		

Sensor model	M-pod		
Air pollutants	CO, CO2, NO2, VOC		
Add. param.	T, RH		
Size (cm):	cca. 15x10	*Data protocol:*	Bluetooth, phone app
Weight (g):		*Portability:*	wearable
Power supply:	Li-battery	*T range (˚C):*	-30-85
Cost ($):	research	*RH range (%):*	5-95
Performance evaluation	Specifications by manufacturers: - components: E2V MICS-5525, CO sensor, ELT S100, CO_2 sensor, E2V MICS-5526, CO and VOC sensor, E2V MICS-4514, CO, VOC and NO_2 sensor Independent evaluation: - During collocation calibrations, median standard errors ranged between 4.0–6.1 ppb for O_3, 6.4–8.4 ppb for NO2, 0.28–0.44 ppm for CO, and 16.8 ppm for CO_2 (Piedrahita et al., 2014)		

Sensor model	[CommonSense Handheld Device]()			
Air pollutants	CO, O_3, NO_x			
Add. param.	T, RH			
Size (cm):		*Data protocol:*	Bluetooth, ph. app	
Weight (g):		*Portability:*	wearable	
Power supply:		*T range (˚C):*		
Cost ($):	research	*RH range (%):*		
Performance evaluation	NA			

Sensor model	[Little Environmental Observatory]()			
Air pollutants	NO, NO_2, O_3			
Add. param.	T, RH			
Size (cm):		*Data protocol:*	Bluetooth, ph. app	
Weight (g):		*Portability:*	wearable	
Power supply:	USB, Li-batt.	*T range (˚C):*		
Cost ($):	research	*RH range (%):*		
Performance evaluation	Specifications by manufacturers: - Alphasense sensors: NO-A4, NO2-A42F, OX-A421 - Communicates with Android app that connects to the sensor unit, reads and upload data to a server (ExpoApp) - Performance assessed within the CITI-SENSE project ([evaluation report]()): poor correlations with reference monitors during field assessments			

Sensor model	Cambridge Personal Sensor (CamPerS)			
Air pollutants	CO, NO, NO_2			
Add. param.	T, GPS			
Size (cm):	18.5x9x3	*Data protocol:*	GPRS	
Weight (g):	450	*Portability:*	wearable	
Power supply:	battery	*T range (˚C):*		
Cost ($):	<600	*RH range (%):*		
Performance evaluation	- EC sensors from Alphasense incorporated CO, NO and NO_2 Independent evaluation: (Jerret et al., 2017) - moderate to high correlations with government monitors - r ~ 0.38–0.8 for NO and CO, r~0.04–0.67 for NO_2 - correlations between the personal sensors and more expensive research instruments were higher than with the government monitors - able to detect high and low air pollution levels in agreement with expectations (e.g., high levels on or near busy roadways and lower levels in background residential areas and parks)			

Portable sensors

Sensor model	MetOne - Aerocet 831		
Air pollutants	PM1, PM2.5, PM4, PM7, PM10 and TSP		
Add. param.			
Size (cm):	15.9x10.2x5x4	*Data protocol:*	RS-232, USB
Weight (g):	900	*Portability:*	portable
Power supply:	7.4V Li-battery	*T range (˚C):*	0-50
Cost ($):	3.000	*RH range (%):*	
Performance evaluation	Specifications by manufacturers: - concentration range: 0-1000 μg/m^3, sample time 1 minute, accuracy: ± 10%, sensitivity: 0.5 μm Independent evaluations: - R^2=0.77 vs. Grimm Model EDM180 PM2.5 monitor (for the PM1 channel), no correlation with T but a significant correlation with RH (Williams et al, 2014a). - r=0.32-0.41 vs. MetOne BAM 1020 FEM PM2.5 monitor (Jiao et al., 2016)		

Sensor model	Aeroqual Series 500 - PM		
Air pollutants	PM10/PM2.5		
Add. param.			
Size (cm):	19.5x12.2x5x4	*Data protocol:*	USB
Weight (g):	<460	*Portability:*	portable
Power supply:	Li-battery	*T range (˚C):*	0-40
Cost ($):	Upon request	*RH range (%):*	10-90
Performance evaluation	Specifications by manufacturers: - Concentration range: 0.000 to 1.000 mg /m^3, LOD: 0.001 mg/m^3, Accuracy of factory calibration: ± (0.002 mg/m3 + 15 % of reading), Resolution: 0.001 mg/^{3}		

Sensor model	Dylos1100/1700		
Air pollutants	PM		
Add. param.			
Size (cm):	12.5×0.9×18.5	*Data protocol:*	USB/RS232
Weight (g):	544	*Portability:*	Portable
Power supply:	120V 60Hz to 9VDC 500mA	*T range (˚C):*	-
Cost ($):	425	*RH range (%):*	-
Performance evaluation	Specifications by manufacturer: -Size ranges: 500 nm and above 2.5μm - LOD<1 ug/m^3, R^2=0.4-0.9 (Rai et al, 2017 and references therein) (Dylos models 1100 Pro and 1700), -Dylos DC1100, time resolution: 1 – min, Dylos vs. Grimm R^2 = 0.81 (AQ-SPEC, 2017)		

Sensor model	Global LoRaWAN		
Air pollutants	CO_2, CO, PM2.5		
Add. param.	T, RH		
Size (cm):	11.3 x0.8 x 0.28	*Data protocol:*	USB
Weight (g):	101	*Portability:*	portable
Power supply:	5V	*T range (˚C):*	-10 - 60
Cost ($):	cca. 222	*RH range (%):*	0 - 85%
Performance evaluation	Specification by manufacturer: -CO_2: Accuracy (at 25°C): ±50 ppm (±3 reading *3%), temperature ±, sensitivity: -132 dBm@980 bps -CO: Accuracy: ±5% or ±20 ppm, range: 0-500 ppm -PM2.5: Range: 0-500 μg/m^3		

Sensor model	Condensation particle counter 3007		
Air pollutants	PM		
Add. param.			
Size (cm):	-	*Data protocol:*	LCD, RS-232 serial data port
Weight (g):	1723	*Portability:*	portable
Power supply:	batteries	*T range (˚C):*	-
Cost ($):	Upon request	*RH range (%):*	-
Performance evaluation	Specification by manufacture: - Particle size range of 0.01 to >1.0 μm, - Concentration range of 0 to 100,000 particles/cm^3		

Sensor model	Aerasene NanoTracer		
Air pollutants	Ultra fine nano particles		
Add. param.	-		
Size (cm):	16.5 x 9.5	*Data protocol:*	USB cable
Weight (g):	750	*Portability:*	portable
Power supply:	Battery	*T range (˚C):*	0-35
Cost ($):	-	*RH range (%):*	0-90%
Performance evaluation	Specification by manufacture: - Detects airborne ultrafine and nanoparticles, 10 to 300 nm.		

Sensor model	P-trak ultrafine particle counter 8525		
Air pollutants	Ultra fine particulate levels		
Add. param.			
Size (cm):	-	*Data protocol:*	TrakPro software
Weight (g):		*Portability:*	Portable/indoor
Power supply:	6AA batt.	*T range (˚C):*	-

Cost ($):	-	*RH range (%):*	-	
Performance evaluation	Specification by manufacture: - ultrafine particles defined as particles having a diameter less than 0.1 µm (or 100 nm).			

Sensor model	Aethalometer AE51 (Magee Scientific)			
Air pollutants	BC (Black carbon)			
Add. param.				
Size (cm):	11.7×0.7×0.16	*Data protocol:*	USB PC with microAethCOM	
Weight (g):	280	*Portability:*	portable	
Power supply:	Li- battery	*T range (˚C):*	0-40	
Cost ($):	-	*RH range (%):*		
Performance evaluation	Specification by manufacture: - Measurement Range: 0-1 mg BC/m3, filter life time dependent on concentration and flow rate setting: - Measurement Resolution: 0.001 µg BC/m^3 - Measurement Precision: ±0.1 µg BC/m3, 1 min avg., 150 ml/min flow rate - good correlation (0.79<R^2<0.94) to more expensive BC/EC instruments, (AQ-SPEC, 2017)			

Sensor model	Aeroqual Series 500 - gases			
Air pollutants	NO_2, O_3 or VOC			
Add. param.				
Size (cm):	19.5x12.2x5x4	*Data protocol:*	USB	
Weight (g):	<460	*Portability:*	portable	
Power supply:	Li-battery	*T range (˚C):*	0-40	
Cost ($):	Upon request	*RH range (%):*	10-90	
Performance evaluation	Specifications by manufacturers: - different seniors for various concentration ranges available (https://www.aeroqual.com/product/series-500-portable-indoor-monitor) Independent evaluations: - NO2: R^2= 0.05-0.90 vs. reference instruments, LOD: 0-60 ug/m^3 (Rai et al., 2017 and references therein) - O3: R^2=0.80-0.95 vs. reference instruments (Rai et al., 2017 and references therein) - R^2=0.83-0.86 vs. SCAQMD FRM instrument (AQ-SPEC, 2017)			

Sensor model	IAQ – CALC Indoor Air Quality Meter (IAQ-CALC™), TSI (Trust Science Innovation), Model 7545 (other models: 7515, 7525, 7535, 7545)			
Air pollutants	CO_2, CO			
Add. param.	Humidity, Temperature			
Size (cm):	8.4 x17.8 x4.4 cm	*Data protocol:*	USB, AC adapter	
Weight (g):	270	*Portability:*	Portable/indoor	
Power supply:	4 size AA-size batteries	*T range (˚C):*	5-45	
Cost ($):	2000	*RH range (%):*	5%-95%	

Performance evaluation	Specification by manufacturer: -CO_2: accuracy: ±3.0% of reading or ±50 ppm, resolution: 1 ppm, response time: 20 seconds -CO (Model 7545 only): sensor type: electro-chemical, range: 0-500 ppm, accuracy: ±3.0% of reading or ±3 ppm, whichever is greater, resolution: 0.1 ppm, response time: <60 seconds to 90% step change

Sensor model	CM-0018, CO2Meter Inc.			
Air pollutants	CO_2			
Add. param.	T, RH			
Size (cm):	14.6×9.1×3.3	*Data protocol:*	USB/Wall Adapter	
Weight (g):	-	*Portability:*	portable	
Power supply:	Li-batt.	*T range (˚C):*		
Cost ($):	400	*RH range (%):*		
Performance evaluation	Specification by manufacture: - Measurement principle: non-dispersive infrared (NDIR): - Measurement Range: 0 – 10,000 ppm (0-1%) - Data logging: 30 seconds to 10 days sampling interval - Accuracy: ± 30ppm ± 3% of measured value			

Stationary/indoors sensors

Sensor model	Air Quality Egg			
Air pollutants	CO2, NO_2/CO, O_3/SO_2, PM2.5 or VOC			
Add. param.	T, RH			
Size (cm):	14x14x85	*Data protocol:*	WI-FI, phone app	
Weight (g):	200g	*Portability:*	Stationary/indoor	
Power supply:	5V micro USB	*T range (˚C):*	0-40(PM),(-20-40)gas	
Cost ($):	280	*RH range (%):*	0-95(PM),(0-100)gas	
Performance evaluation	Specifications by manufacturers: - detects 0.5 - 10 µm PM sizes using Shinyei PPD 60 sensor, electrochemical Spec Sensors used for gases, max sensor response time: 30 seconds Independent evaluations: - PM: r=-0.06-0.4 versus MetOne BAM 1020 FEM PM2.5 monitor (Jiao et al., 2016) - NO2: r=-0.25-0.22 versus Thermo Fisher Scientific FEM 42C (Jiao et al., 2016) -CO: R^2~0.0 with the corresponding FRM data (AQ-SPEC, 2017) -O_3: R^2<0.20 with corresponding FRM data (AQ-SPEC, 2017) -$PM_{2.5}$ vs. FEM GRIMM PM2.5 R^2> 0.82 (AQ SPEC, 2017), PM data correlate well with the FEM PM2.5 data from both the GRIMM and the BAM, seem to track the diurnal PM2.5variations provided by the FEM instruments (AQ SPEC, 2017)			

Sensor model	Netatmo Weather Station			
Air pollutants	CO			
Add. param.	Temperature, RH, Noise, GPS			
Size (cm):	4.5x4.5x15.5/ 4.5x4.5x10.5	*Data protocol:*	Wi-Fi	
Weight (g):		*Portability:*	Stationary/Indoor	

Power supply:	USB wall adapter/ AAA batt.	*T range (˚C):*	Indoor 0-50, Outdoor -40-65	
Cost ($):	170	*RH range (%):*	0-100	
Performance evaluation	Specifications by manufacturer: - Detailed 7-days weather forecast - Light indicator for direct CO2 reading - Accessible from multiple devices, Smartphone app			

Sensor model	Foobot			
Air pollutants	CO_2, VOCs, PM, RH			
Add. param.	Temperature			
Size (cm):	17.2x7.1	*Data protocol:*	Wi-fi	
Weight (g):	475	*Portability:*	Stationary/Indoor	
Power supply:	USB power adaptor	*T range (˚C):*	15-45	
Cost ($):	200	*RH range (%):*	30-85	
Performance evaluation	Specifications by manufacturer: - Foobot's optical sensor detects particles in the air from 0.003 to 2.5µg - Sensibility: particulate size 0.3 µm to 2.5 µm (PM 2.5) - Range 0 to 1 300 µg/m³ ; Precision ±4µg or ±20% Total VOC: - MOS sensor tech. automotive industry grade Connectivity: - Story data every 5 min to cloud, on demand instant measurements Independent evaluations: - demonstrated a modest correlation (R^2 ~ 0.55) with the FEM instrument and moderately overestimated the FEM (BAM) measurement data (AQ-SPEC, 2017)			

Sensor model	CUBE			
Air pollutants	VOCs, PM, RH,			
Add. param.	Temperature, Light, Noise			
Size (cm):	5x5x5	*Data protocol:*	Bluetooth low energy, ZigBee	
Weight (g):	70	*Portability:*	Stationary/Indoor	
Power supply:	Micro USB	*T range (˚C):*		
Cost ($):	160	*RH range (%):*		
Performance evaluation	Specifications by manufacturer: - PM sensors for dust and cigarette smoke; - Volatile Organic Compounds (Alcohols, Aldehydes, Aliphatic hydrocarbons, Amines, Aromatic hydrocarbons, CO, CH4, LPG, Ketones and Organic acids) sensors, converted to CO_2 equivalent ppm - Smartphone app			

Sensor model	Smart Citizen Kit			
Air pollutants	CO, NO_2			
Add. param.	T, RH, light, noise			
Size (cm):	Cca.15x15x5	*Data protocol:*	WI-FI, phone app	
Weight (g):		*Portability:*	Stationary/indoor	
Power supply:	3.7V Li-battery	*T range (˚C):*		

Cost ($):	~220	*RH range (%):*		
Performance evaluation	Specifications by manufacturers: -MiCS-4514 MOC sensors used (https://github.com/fablabbcn/Smart-Citizen-Kit/wiki/Datasheets/MiCS-4514_CO_NO2.pdf) -Concentration range: CO: 1-1000 ppm, NO2: 0.05-5 ppm Independent evaluation: - CO: R^2=0.45-0.84 vs. SCAQMD FRM instruments, NO_2 concentrations not reliable (AQ-SPEC, 2017)			

Sensor model	[Speck]			
Air pollutants	PM2.5			
Add. param.	T, Speck 2.0 also RH			
Size (cm):	11.4x8x9.4	*Data protocol:*	WI-FI, phone app	
Weight (g):	165	*Portability:*	Stationary/indoor	
Power supply:	5V micro USB	*T range (˚C):*	-10 - 65	
Cost ($):	150	*RH range (%):*	<95	
Performance evaluation	Specifications by manufacturers: - Size range of detected particles 0.5 – 3 microns using DSM501A Dust Sensor Independent evaluations: - R^2<0.1 when comparing Speck vz2 vs Grimm Model EDM180 PM2.5 monitor, impact of T and RH observed (Williams et al., 2016)			

Sensor model	[Aretas Sensor Network]			
Air pollutants	CO, CO_2, NO_2, O_3, VOC, PM (0.3, 0.5, 1, 2.5, 5, 10 um)			
Add. param.	T, RH, noise, GPS			
Size (cm):		*Data protocol:*	Wi-FI, phone app	
Weight (g):		*Portability:*	Stationary/indoor	
Power supply:	6xAA/5V miniUSB	*T range (˚C):*		
Cost ($):	Upon request	*RH range (%):*		
Performance evaluation	Specifications by manufacturer: - CO_2: 0 – 10,000 ppm, Resolution: 1 ppm; Sensitivity: ± 20 ppm, Accuracy: ± 30 ppm - NO_2: 0 - 20 ppm, Resolution: 0.1 ppm, Accuracy of Calibration: <0.9 ppm, - O_3: 20 - 200 ppb of ozone (O3), Response time: 30 seconds, Accuracy: < ± 2 % of reading - VOC: T range: -20 to +40 °C, RH range: 0 to 90%, Measurement Range: up to 10,000 ppm, Response Time: < 5 seconds Minimum Detectable Quantity: as low as 1 ppb - PM: Sensor Measurement: 0.3, 0.5, 1, 2.5, 5, 10 um, Particle Counting Accuracy: 50% @ 0.3um, 98% @ >0.5um, Sensor Response Time: < 10s			

Sensor model	[Airthinx]			
Air pollutants	CO_2, VOC, CH_2O, PM 1, PM 2.5, PM 10			
Add. param.	T, RH, pressure			
Size (cm):	11x7x3	*Data protocol:*	Wi-FI, Bluetooth, Mesh, Cell., ph. app	
Weight (g):	180	*Portability:*	Stationary/indoor	
Power supply:	5V micro-USB	*T range (˚C):*	-30-75	
Cost ($):	Upon request	*RH range (%):*		

Performance evaluation	Specifications by manufacturer: - CO_2: - 0~3000 ppm, Resolution - 1 ppm, Maximum Consistancy Error - ±50ppm+5%FS, Single Response Time - < 3 sec., Total Response Time - ≤ 25 sec. - TVOC: - 1~30ppmof EtOH, Sensitivity - 0.15 ~ 0.5 Rs (10ppm of EtOH)/ Rs (air) - PM: Effective Range 0~500 μg/m^3, Resolution 1 μg/m^3, Efficiency 98%>=0.5μm, Maximum Consistency Error ±10% @100~500 μg/m^3

Sensor model	AIRASSURE PM2.5			
Air pollutants	PM2.5			
Add. param.				
Size (cm):	16.2x8.5x3.3	*Data protocol:*	Ethernet	
Weight (g):	200	*Portability:*	Stationary/indoor	
Power supply:	24V (AC or DC)	*T range (˚C):*	10-30	
Cost ($):	~1000	*RH range (%):*	<65	
Performance evaluation	Specifications by manufacturer: - R^2=0.95 versus TEOM PM2.5 monitor - R^2>0.81 Air Assure Pm2.5 vs. FEM GRIMM data (AQ-SPEC, 2017)			

Stand-alone sensors

In Table 3 a summary of most common micro-sensors used in the above listed ready-to-use modules, and which were at least partly evaluated in scientific literature is given. The summary is based on a recent review of sensor technologies by Rai et al. (2017) and focused on field evaluations of sensors.

Table 3: Characteristics of the most common micro sensors (adopted from Rai et al., 2017))

Pollutant	**Model**	**Sensor Type**	**LOD (μg/m^3 for PM, ppb for O_3, μg/m^3 for NO_2)***	**R^2 range*** **
PM	Alphasense OPC-N2	Optical	NA	
	Plantower PMS 1003	Optical		
	Plantower PMS 3003	Optical	0.721-10.5	0.83-0.95
	Samyoung DSM501A	Optical	4.28-11.4	
	Sharp DN7C3CA006	Optical	10	0.08-0.45
	Sharp GP2Y1010AU0F	Optical	NA	
	Shinyei PPD42NS	Optical	26.1-26.9	
	Shinyei PPD60PV	Optical	4.59-6.44	0-0.98
	SPEC Sensors, LLC 968-001	Optical	NA	0.44-0.46
NO_2	NO2_3E50	EC	**	0.01-0.90
	NO2-B4	EC	**	0.05-0.9
	NO2-A1	EC	**	0.88-0.92
	NO2 ANA	EC	**	0.02-0.9
	MICS-4514	MOS	**	0.2-0.8
	MICS-2710	MOS	**	
O_3	Aeroqual SM50	MOS	NA	0.80-0.95
	SGX MICS OZ-47	MOS	1.5	0.80-0.82
	SGX MICS 2610	MOS	0.5	0.11-12
	SGX MICS 2611	MOS	5.1-11.7	
	FIS SP-61	MOS	NA	

	Alphasense O3B4	MOS	6.8	0.13-0.70
	Citytech O3_3E1F	EC	2.7	0.85-0.9
	Alphasense OX-B421	EC)	1.8	0.01-0.7
CO	TSG-5042	EC		0.19-0.30
	CO-B4	EC		0.55-0.95
	MICS-4514	MOS		0.78-0.8
	MICS-5525	MOS		0.01-0.19
	MQ-7	MOS		
	SPEC Sensors, LLC 968-001			

NA-not available; EC – electrochemical sensor; MOS - metal-oxide-semiconductor sensor,
** Based on references in Rai et al. (2017);*
*** Range of LOD for EC: 0-60 µg/m3, range of LOD for MOS: 2-10 µg/m*^{3} *(estimated based on Figure 2 in Rai et al., 2017);*
**** comparison with reference instruments during field testing based on Rai et al. (2017) and references therein*

3.2.2 Personal activity sensors

Sensor model	FitBit Flex			
Type	Physical Activity			
Cost ($)	80			
Steps	X	*Heart Rate*		
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	FitBit Charge 2			
Type	Physical Activity			
Cost ($)	90			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	FitBit Surge			
Type	Physical Activity			
Cost ($)	200			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*	X	
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	Garmin Vivosmart HR+			
Type	Physical Activity			
Cost ($)	140			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*	X	
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	Garmin vívoactive			
Type	Physical Activity			
Cost ($)	220			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*	X	

Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	[Samsung Gear Fit 2](#)			
Type	Physical Activity			
Cost ($)	130			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*	X	
Sleep	X	*Temperature*		
Respiration		*Light*		

Sensor model	[Huawei Fit](#)			
Type	Physical Activity			
Cost ($)	130			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	[Jawbone UP3](#)			
Type	Physical Activity			
Cost ($)	40			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	[Withings Pulse](#)			
Type	Physical Activity			
Cost ($)	100			
Steps	X	*Heart Rate*	X	
Active minutes		*Oximetry*	X	
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	[Misfit Ray](#)			
Type	Physical Activity			
Cost ($)	80			
Steps	X	*Heart Rate*		
Active minutes		*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*	X	
Sensor model	[Misfit Shine 2](#)			
Type	Physical Activity			
Cost ($)	80			
Steps	X	*Heart Rate*		
Active minutes		*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*	X	

Sensor model	TomTom Fitness Tracker			
Type	Physical Activity			
Cost ($)	80			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	TomTom Runner 3			
Type	Physical Activity			
Cost ($)	170			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*	X	
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	Apple Watch			
Type	Physical Activity			
Cost ($)	450			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	Moov Now			
Type	Physical Activity			
Cost ($)	50			
Steps	X	*Heart Rate*		
Active minutes	X	*Oximetry*		
Calories/Energy		*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	Actiwatch 2 - Philips Respironics			
Type	Physical Activity			
Cost ($)				
Steps	X	*Heart Rate*		
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*	X	
Sensor model	Actigraph wGT3X-BT Monitor			
Type	Physical Activity			
Cost ($)				
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*	X	
Sleep	X	*Temperature*		
Respiration		*Light*	X	
Sensor model	Mimobaby Tracker			
Type	Physical Activity			
Cost ($)	200			
Steps	X	*Heart Rate*		
Active minutes		*Oximetry*		
Calories/Energy		*GPS*	X	
Sleep	X	*Temperature*	X	

Respiration	X	*Light*		
Sensor model	[iDEEA system](#)			
Type	Physical Activity			
Cost ($)				
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep		*Temperature*		
Respiration	X	*Light*		
Sensor model	[Basis Peak](#)*			
Type	Physical Activity			
Cost ($)	100			
Steps	X	*Heart Rate*	X	
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	[Microsoft Band](#)*			
Type	Physical Activity			
Cost ($)	150			
Steps	X	*Heart Rate*	X	Source: https://kbdevstorage1.blob.core.windows.net/asset-blobs/4000512_en_1
Active minutes	X	*Oximetry*		
Calories/Energy	X	*GPS*		
Sleep	X	*Temperature*		
Respiration		*Light*		
Sensor model	[Zephyr Pebble Watch +](#)			
Type	Physical Activity			
Cost ($)	650			
Steps	X	*Heart Rate*	X	
Active minutes		*Oximetry*		
Calories/Energy	X	*GPS*		Source: https://www.zephyranywhere.com/img/zephyr/product/pebble-watch-with-zephyr-software-preloaded-
Sleep		*Temperature*		
Respiration	X	*Light*		

3.3 Findings

3.3.1 General features of personal sensors

Based on the review of sensors specifications given in section 3.2 and considering the specific objectives of the ICARUS, the following observations on general features of the sensors available are made.

<u>AQ sensors</u>

- Most of the sensors available on the market are designed to measure PM of various sizes, while among gaseous pollutants focus in mostly on NO_2, O_3 and CO. PM is measured using light scattering methods, while gaseous pollutants are measured using either electrochemical or metal-oxide sensors.
- A vast majority of ready-to-use modules enables detection of additional general environmental parameters, mostly temperature and relative humidity, and which could help during eventual subsequent signal processing.

- Sensors are reported to perform over a wide range of environmental conditions, usually in 0-40° C and 20-90 %RH range, respectively.
- Most of the ready-to-use modules measure at least two air pollutants. Some commercially available modules require selection of one or combination of sensors of interest.
- Data capturing and transfer protocols: depending on the sensor design the data retrieval and access varies from simple integrated data loggers and USB data transfers to real-time on-line communication via Wi-Fi and Bluetooth interfaces. Advanced systems like dedicated web portals/interfaces allow users to not only download raw sensor data, but also to stream pollution information in real time, visualize this data in easy-to-understand contour-like pollution maps, and gather statistical information about pollutants over a specified spatiotemporal region (Hedgecock et al., 2012).
- Sensors specifically designed to be wearable can communicate via its Wi-Fi or Bluetooth interface with smartphone applications and in this way enable collection and display on high-resolution data in real-time as well as on-line transfer and storage of data. These devices also track location by either GPS integrated in the device or from accompanying smartphone.
- Wearable devices are usually designed in a user friendly manner with all the necessary accessories.
- Compared to wearable devices, ready-to-use modules designed as portable only can display the data in real-time on the integrated display, however usually do not enable tracking of the location and store the data to integrated data loggers which requires subsequent transfer of data to a computer via USB or similar. They are also not designed to be carried around by individual for longer period of time.
- Several ready-to-use modules are designed and available as stationary devices for indoors home environment sensing. These devices are usually connected to the household's Wi-Fi network and synced to the online account.
- Community based monitoring: some of the sensing devices (e.g. Everyaware SensorBox, Air Quality egg, NetAtmo etc.) work on the principles of crowdsourced citizen monitoring and are connected through dedicated web applications and portals where community of users can share and access the data gathered.
- Stand-alone sensors: number of various micro-senor components that can be integrated in custom made data acquisition and storage system are available. Several of them were at least partly tested under field conditions (Table 3).

<u>Physical activity sensors</u>

There are numerous types of low-cost physical activity sensors available which enable measuring or estimation of various combinations of parameters such as location, number of steps, active minutes, calories/energy, sleep, respiration, heart rate, oximetry, etc. Most of these devices available on the market communicate via Bluetooth or Wi-Fi interface with smartphone applications.

3.3.2 Summary of AQ sensors performance assessment

In addition to sensor specific information and performance evaluation in section 3.2, in this section the overview of the most important outcomes of sensors performance evaluations from various sources including environmental agencies (e.g. Williams et al., 2014a, 2014b, 2015; AQ-SPEC, 2017) and scientific literature (e.g. Piedrahita et al., 2014; Jiao et al, 2016) including literature reviews (Rai et al., 207) is given, as follows.

The performance of some of the sensors from the above lists was tested under either laboratory or field conditions or both. Whatever the experimental setup, for most of the sensors testing and evaluation was performed in a very limited extent, usually focusing on the comparisons with reference monitors for short periods of time and covering a narrow range of environmental conditions only. Regardless of the extent and type of evaluations, findings by all authors are similar.

When low-cost sensors are evaluated under controlled laboratory conditions, authors usually report a very good agreement with more sophisticated and more expensive instruments. For example, Williams et al. (2014b) evaluated various NO_2 and O_3 both metal-oxide and electrochemical sensors using an exposure chamber linked with FRM/FEM instrumentation. Some of the most important outcomes of their laboratory trails are as follows: fast response times with minimal rise and lag times; high degree of linearity over full response range; detection limits lower than FRM/FM instrumentation, however near environmental relevant levels; co-response to other pollutants and extremes in RH and temperature.

On the other hand, it is known that laboratory calibrations are not suitable for low-cost sensors, as they do not reflect environmental conditions during actual deployment and therefore suffer from bias (e.g. Piedrahita et al., 2014).

Along these lines, for the low-cost sensors for monitoring of particulate matter, Rai et al. (2017) in their review emphasise a huge gap in the scientific literature related to calibration and performance assessment of such sensors. Moreover, they warn against direct use of laboratory calibrated sensors, as in real-world conditions changing conditions of particle compositions, sizes, and environmental factors can drastically impact a sensor's response. Therefore, it was suggested for PM sensors to be calibrated frequently to have a control over long-term performance and under conditions as close to the final deployment (Rai et al., 2017).

Similar, for the low-cost sensors for monitoring of gaseous pollutants, Rai et al. (2017) reviewed performance of various metal-oxide-semiconductor (MOS) and electrochemical (EC) sensors as reported in scientific studies. The overall conclusions are: MOS sensors are cheaper but consume more power; for O_3 measurements MOS sensors seem to provide better agreement with reference instruments and do not suffer from cross-interferences with NO_2, whereas EC O_3 sensors have faster response time; there is not enough evidence of performance of NO_2 and CO sensor to be feasible to make recommendation. As for the PM sensors, frequent calibration under conditions close to deployment is advised (Rai et al., 2017).

Overall, it seems that currently there is a consensus regarding the use of commercial low-cost sensors as recently highlighted by Castell et al. (2017), namely that (i) commercial low-cost sensors have to be evaluated under diverse environmental conditions prior deployment, (ii) are not ready for applications that require high accuracy, however can (iii) provide relative and aggregated information about the observed air quality.

4 Conclusions

This report presents a systematic review of latest advances in the use of sensor technologies for defining external exposure at individual level, with a focus on the use of air quality and physical activity sensors. Review was conducted in two steps. Initially, following Extensive Literature Search principles, the focus was on scientific literature reporting application of such sensor technologies. In the next step, new information sources were included and the review was extended to include information on sensor characteristics and performance. Overall, the following conclusions can be drawn:

- New sensor technologies are being used increasingly in practice to assess exposure of individuals. The ability to monitor personal exposure using low-cost, portable and easy to use sensors has the potential to provide citizens and communities with the opportunity to directly monitor phenomena that can benefit their lives and wellbeing (Huck et al., 2016). Indeed, some authors measured and reported change in perceptions and consequent change in behaviour of some of the participants over the course on their involvement using such devices (Sirbu et al., 2015; Piedrahita et al., 2014), resulting in their increased awareness (Vagnoli et al., 2014).

- There is, however, still quite a few drawbacks in the current state of art that have to be considered when using these new devices. One of the most important disadvantages is the fact that the majority of the available low-cost technologies for air quality are still in testing phase and without clearly demonstrated fitness of purpose. This is in a big part a result of challenges related to quality control of the results obtained by these devices, e.g. efficient pre-calibration of sensors reflecting environmental conditions during the deployment.

- The following is suggested to be considered for collection of multi-sensor data for personal exposure monitoring foreseen within ICARUS: Ideally, multi-sensor setup should comprise environmental, location and personal movement/activity data, combined in user friendly, easy to use "package". Location tracking is essential component in exposure assessment. Smartphones with built-in GPS can do the job. The suggested environmental parameter is particulate matter (preferably PM2.5 or UFM), as it is widely recognized as a pollutant of concern in urban environments, there is commercial availability of such sensors and mainly due to the fact that use of such devices was most efficiently tested and demonstrated in existing studies. Among the gaseous pollutants, for the same reasons, NO_2, O_3 and CO are suggested. Regardless of the device used, it should be pre-calibrated, preferably using the co-location approach under same environmental conditions as during the deployment. A multi-platform data collection tool should be developed in order to store, manage and process all data coming from different devices.

Table with studies included in ELS:

Name	Year	Journal
Adams et al.	2009	Journal of Environmental Monitoring
Arvind et al.	2016	19th Conference on Digital System Design
Bales et al.	2012	6th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2012
Boogaard et al.	2009	Atmospheric Environment
Borrego et al.	2015	Urban Climate
Buonanno et al.	2014	Science of Total Environment
Chen et al.	2012	Atmospheric Environment
Dalla Valle et al.	2017	International Journal of Sustainable Development and Planning
Dario et al.	2010	EESMS 2010 - 2010 IEEE Worskshop on Environmental, Energy, and Structural Monitoring Systems, Proceedings
de Nazelle et al.	2013	Environmental Pollution
Delgado-Saborit et al.	2012	Journal of Environmental Monitoring
Dons et al.	2011	Atmospheric Environment
Douglas Black et al.	2000	Environmental Science and Technology
Fathallah et al.	2016	13th IEEE Annual Consumer Communication and Networking conference
Gall et al.	2016	Building and environment
Hedgecock et al.	2010	Proceedings of the Annual Southeast Conference
Hu et al.	2014	ACM International Conference Proceeding Series
Hu et al.	2014	IEEE 9th International conference on intelligent sensors, sensor networks
Huck et al.	2017	Environmental monitoring and assessment
Jiang et al.	2013	AI MAGAZINE
Kanjo et al.	2008	Personal and ubiquitous computing
Loh et al.	2017	International Journal of Environmental Research and Public Health
Lu et al.	2015	ISPRS International Journal of Geo-Information
Marek et al.	2016	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives
Mead et al.	2013	Atmospheric Environment
Nieuwenhuijsen et al.	2016	Environmental Health
Nieuwenhuijsen et al.	2015	Environmental Science and Technology
Nieuwenhuijsen et al.	2014	International Journal of Environmental Research and Public Health
Nyhan et al.	2014	Science of Total Environment
Piedrahita et al.	2014	Atmospheric measurement techniques
Pilla et al.	2015	Sustainable Cities and Society
Predic et al.	2013	IEEE International conference on pervasive computing and communications workshops

Rabinovitch et al.	2016	Environmental Health: A Global Access Science Source
Rodes et al.	2012	Atmospheric environment
Ryan et al.	2015	The science of the total environment
Sarigiannis and Gotti	2014	Pneumologia pediatrica
Seto et al.	2009	Proceedings - 2009 IEEE International Symposium on Industrial Embedded Systems, SIES 2009
Sirbu et al.	2015	PLoS ONE
Snik et al.	2014	Geophysical Research Letters
Steinle et al.	2013	Science of the Total Environment
Steinle et al.	2015	Science of Total Environment
Thai et al.	2008	Science of Total Environment
Vagnoli et al.	2014	IET Seminar Digest
Wu et al.	2010	American Journal of Epidemiology
Wu et al.	2012	Environmental health
Yang et al.	2016	Lecture Notes in Computer Science
Yi et al	2015	Sensors (Switzerland)
Zeiger & Huber	2014	IPSN 2014 - Proceedings of the 13th International Symposium on Information Processing in Sensor Networks (Part of CPS Week)
Zwack et al.	2012	Atmospheric Environment

Other references used:

AQ-SPEC, 2017. Field Evaluation of Low-Cost Air Quality Sensors, http://www.aqmd.gov/aq-spec/evaluations/field

Castell, N., Dauge, F.R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., Bartonova, A., 2017. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ. Int. 99, 293–302.

EFSA, 2010. Application of systematic review methodology to food and feed safety assessments to support decision making http://onlinelibrary.wiley.com/doi/10.2903/j.efsa.2010.1637/epdf

Jensen, B. B. 2016. Extensive Literature Search on the “Effects of Copper intake levels in the gut microbiota profile of target animals, in particular piglet”. EFSA supporting publication 2016:EN-1024. 68 pp.

Jerrett, M., Donaire-Gonzalez, D., Popoola, O., Jones, R., Cohen, R.C., Almanza, E., de Nazelle, A., Mead, I., Carrasco-Turigas, G., Cole-Hunter, T., Triguero-Mas, M., Seto, E., Nieuwenhuijsen, M. 2017, Validating novel air pollution sensors to improve exposure estimates for epidemiological analyses and citizen science, Environmental Research, 158, 286-294.

Jiao, W., Hagler, G., Williams, R., Sharpe, R., Brown, R., Garver, D., Judge, R., Caudill, M., Rickard, J., Davis, M., 2016. Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. Atmos. Meas. Tech. 9, 5281–5292.

Kocman et al., 2016. Literature reviewing protocol. Internal ICARUS document, available at: http://icarus2020.eu/milestones/

Lerner, U., Yacobi, T., Levy, I., Moltchanov, SA., Cole-Hunter, T., Fishbain, B. 2015, The effect of ego-motion on environmental monitoring. Science of the total environment, 15, 533:8-16.

Lewis, A. and Edwards, P., 2016, Validate personal air-pollution sensors, Nature, Vol. 535, 29.

Loh et al., 2014. Can Sensor Technologies Really Define the Exposome? HEALS (FP7-ENV-2013-603946) report.

Rai, A. C., Kumar, P., Pilla, F., Skouloudis, A. N., Di Sabatino, S., Ratti, C., Yasar, A., Rickerby, D. 2017, End-user perspective of low-cost sensors for outdoor air pollution monitoring. Science of the total environment 607-608, 691-705.

Williams, R., A. Kaufman, T. Hanley, J. Rice, AND S. Garvey. Evaluation of Field-deployed Low Cost PM Sensors. U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-14/464 (NTIS PB 2015-102104), 2014a.

Williams, R., R. Long, M. Beaver, A. Kaufman, F. Zeiger, M. Heimbinder, I. Hang, R. Yap, B. Acharya, B. Ginwald, K. Kupcho, S. Robinson, O. Zaouak, B. Aubert, M. Hannigan, R. Piedrahita, N. Masson, B. Moran, M. Rook, P. Heppner, C. Cogar, N. Nikzad, AND W. Griswold. Sensor Evaluation Report. U.S Environmental Protection Agency, Washington, DC, EPA/600/R-14/143 (NTIS PB2015-100611), 2014b.

5 Appendix A - AQ studies exclusion/inclusion flow chart

Legend

Scientific paper

Conference proceeding

Review paper

Rejected during initial screening

Rejected after full text reading

Full paper not accessible

ID	Name	Year	Journal	Type of paper			Rejected	
				PAP	PRO	REW	Phase 1	Phase 2
S11	Alba	2016	Intelligent systems for smart cities					
WS10	Arco et al.	2016	First international conference on smart data and smart cities					
WS12	Arvind et al.	2016	19th Conference on Digital System Design					
S84	Bales et al.	2012	6th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2012					
S124	Baraton et al.	2004	Journal of Nanoparticle Research					
S121	Barbara et al.	2005	12th International Congress on Sound and Vibration 2005, ICSV 2005					
S74	Birmni et al.	2013	Meteorologische Zeitschrift					
S126	Black et al.	2000	Environmental Science and Technology					
S4	Book of abstracts	2017	International Symposium on Ubiquitous Networking, UNet 2016					
S41	Book of abstracts	2015	Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST					
S44	Book of abstracts	2014	2013 International Conference on Biomedical Engineering and Environmental Engineering, ICBEEE 2013					
S45	Book of abstracts	2013	2013 2nd International Conference on Sustainable Energy and Environmental Engineering, ICSEEE 2013					
S47	Book of abstracts	2014	Advanced Materials Research					
S61	Book of abstracts	2014	International Conference on Sensors Instrument and Information Technology, ICSIIT 2014					
S62	Book of abstracts	2014	International Conference on Materials Science and Computational Engineering, ICMSCE 2014					
S27	Borrego et al	2015	Urban Climate					

S64	Budde et al.	2013	ISWC 2013 - Proceedings of the 2013 ACM International Symposium on Wearable Computers					
S36	Capezzuto et al	2015	Lecture Notes in Electrical Engineering					
S23	Carter et al.	2016	ECS Transactions					
S28	Castell et al.	2015	Urban Climate					
S86	Chen et al.	2012	Atmospheric Environment					
WS25	Ciuzas et al.,	2015	Atmospheric environment					
S2	Dalla Valle et al.	2017	International Journal of Sustainable Development and Planning					
S103	Dario et al.	2010	EESMS 2010 - 2010 IEEE Worskshop on Environmental, Energy, and Structural Monitoring Systems, Proceedings					
WS4	Deary et al.	2016	Air quality atmosphere and health					
S87	Delgado-Saborit	2012	Journal of Environmental Monitoring					
S107	Dutta et al.	2009	Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems, SenSys 2009					
PM2	Elen et al	2012	Sensors					
WS16	Fathallah et al.	2016	13th IEEE Annual Consumer Communication and Networking conference					
WS2	Fishbain et al.	2017	Science of total environment					
WS6	Gall et al.	2016	Building and environment					
WS61	Gameiro et al	2012	PROCEEDINGS OF THE ACM WORKSHOP ON HIGH PERFORMANCE MOBILE OPPORTUNISTIC SYSTEMS					
WS11	Gao et al.	2016	IEE 35th annual international conference on computer communications					
S106	Groneberg et al.	2010	Journal of Occupational Medicine and Toxicology					
S8	Gugliermetti et al.	2016	IEEE 2nd International Smart Cities Conference: Improving the Citizens Quality of Life, ISC2 2016					
WS21	Guo et al.,	2016	Journal of sensors					
S91	Hasenfratz	2012	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)					
S59	Hasenfratz et al	2014	IEEE International Conference on Pervasive Computing and Communications					
WS39	Hasenfratz et al	2015	PERVASIVE AND MOBILE COMPUTING					
S77	Hasenfratz et al.	2013	Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems					
S78	Hasenfratz et al.	2013	Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems					

S102	Hedgecock et al.	2010	Proceedings of the Annual Southeast Conference					
S104	Hedgecock et al.	2010	Proceedings of the ACM Symposium on Applied Computing					
S110	Hodges	2009	Traffic Engineering and Control					
S117	Hodges et al.	2009	16th ITS World Congress					
WS49	Hori et al	2013	ENVIRONMENTAL HEALTH AND PREVENTIVE MEDICINE					
S112	Hou	2009	Journal of Networks					
WS37	Hromic et al	2015	IEEE INTERNATIONAL CONFERENCE ON COMMUNICATIONS (ICC) Book Series					
S42	Hu et al	2014	ACM International Conference Proceeding Series					
WS40	Hu et al	2014	IEEE NINTH INTERNATIONAL CONFERENCE ON INTELLIGENT SENSORS, SENSOR NETWORKS AND INFORMATION PROCESSING					
WS22	Hu et al.,	2016	Peruasine and mobile computing					
S40	Huber and Wollenstein	2015	Proceedings of SPIE - The International Society for Optical Engineering					
S6	Jangid & Sharma	2016	3rd International Conference on Computing for Sustainable Global Development, INDIACom 2016					
WS70	Jantunen et al	1999	CHEMOSPHERE					
WS51	Jiang et al	2013	AI MAGAZINE					
S95	Jiang et al.	2011	Proceedings of the 2011 ACM Conference on Ubiquitous Computing					
WS66	Kilgus	2009	GEFAHRSTOFFE REINHALTUNG DER LUFT					
S125	Kinkade et al.	2000	Proceedings of SPIE - The International Society for Optical Engineering					
WS71	Klepeis et al	1999	JOURNAL OF EXPOSURE ANALYSIS AND ENVIRONMENTAL EPIDEMIOLOGY					
WS8	Kotsev et al.	2016	Sensors					
S3	Koval & Iryogen	2017	Advances in Intelligent Systems and Computing					
S123	Le Moullec	2004	Petrole et Techniques					
S70	Lee et al.	2013	Sensors and Actuators, B: Chemical					
WS27	Lee et al.,	2015	International Journal of computers communications and control					
WS24	Lerner et al.,	2015	Science of total environment					
WS5	Li et al.	2015	IEE transactions on biomedical circuits and systems					
S32	Liu et al	2015	Proceedings - IEEE INFOCOM					

WS19	Liu et al.	2016	3rd international conference on Materials, Engineering, Manufacturing technology					
S90	Liu et al.	2012	International Journal on Smart Sensing and Intelligent Systems					
S93	Liu et al.	2011	Proceedings of the International Conference on Sensing Technology, ICST					
S127	Loh et al.	2017	International Journal of Environmental Research and Public Health					
S56	Lo Re et al	2014	Advances in Intelligent Systems and Computing					
S34	Lu et al.	2015	ISPRS International Journal of Geo-Information					
S82	Ma et al.	2012	CICTP 2012: Multimodal Transportation Systems - Convenient, Safe, Cost-Effective, Efficient - Proceedings of the 12th COTA International Conference of Transportation Professionals					
WS3	Magno et al.	2016	IEEE Sensor Journal					
WS63	Mahyuddin et al	2010	BUILDING AND ENVIRONMENT					
S22	Marek et al	2016	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives					
WS35	Marjavi et al.,	2015	IEEE International Conference					
PM1	Marques et al.	2016	Int J Environ Res Public Health					
WS14	Marques et al.	2016	11th Iberian Conference on Information Systems					
WS52	Mead et al	2013	ATMOSPHERIC ENVIRONMENT					
WS17	Mehta et al.	2016	3rd international Conference on big data and smart cities					
WS1	Mikuckas et al.	2017	Applied mathematical modeling					
S48	Mitreska et al	2014	Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST					
WS13	Moore et al.	2016	BMJ Open					
WS33	More et al.,	2015	IEE international conference on comuptational inteligance and computer research					
WS9	Mueller et al.	2016	Atmospheric environment					
W65	Ni et al	2009	TRANSACTIONS OF THE ASABE					
WS7	Nieuwenhuijsen et al	2016	Environmental Health					
S81	Nikzad et al.	2012	Proceedings - Wireless Health 2012, WH 2012					
WS31	Oletic et al.,	2015	IEEE Sensors Applications Symposium (SAS)					

S53	Othman et al	2014	4th International Conference on Digital Information and Communication Technology and Its Applications, DICTAP 2014					
WS48	Paprotny et al	2013	SENSORS AND ACTUATORS A-PHYSICAL					
S118	Paradiso et al.	2008	Proceedings of the 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS'08 - "Personalized Healthcare through Technology"					
S49	Penza et al	2014	Proceedings of IEEE Sensors					
WS42	Piedrahita et al	2014	ATMOSPHERIC MEASUREMENT TECHNIQUES					
WS26	Pilbe et al.,	2015	Sustainable cities and society					
S57	Pino & Costanzo	2014	Proceedings of the International Conference on Physiological Computing Systems					
WS32	Postalache et al.,	2015	6th International conference on inteligance, systems and applications					
S114	Postolache et al.	2009	International Journal of Advanced Media and Communication					
S89	Postolache et al.	2012	International Multi-Conference on Systems, Signals and Devices, SSD 2012 - Summary Proceedings					
S92	Postolache et al.	2011	Joint IMEKO TC11-TC19-TC20 Int. Symp. Metrological Infrastructure, Environmental and Energy Measurement and Int. Symp. of Energy Agencies of Mediterranean Countries, IMEKO-MI 2011					
S19	Postolatche et al	2016	IISA 2015 - 6th International Conference on Information, Intelligence, Systems and Applications					
WS56	Predic et al	2013	IEEE INTERNATIONAL CONFERENCE ON PERVASIVE COMPUTING AND COMMUNICATIONS WORKSHOPS					
WS68	Pummakarnchana et al	2005	SCIENCE AND TECHNOLOGY OF ADVANCED MATERIALS					
WS20	Qian et al.	2016	Journal of ambient intelligence and smart environments					
S55	Qiao	2014	Applied Mechanics and Materials					
S46	Rachelin Sujae et al	2014	World Applied Sciences Journal					
S99	Ramanathan et al	2011	Atmospheric Environment					
S58	Riga & Karatzas	2014	ACM International Conference Proceeding Series					

WS46	Riga et al	2014	4TH INTERNATIONAL CONFERENCE ON WEB INTELLIGENCE, MINING AND SEMANTICS					
WS45	Rizea et al	2014	ROEDUNET CONFERENCE 13TH EDITION: NETWORKING IN EDUCATION AND RESEARCH JOINT EVENT RENAM 8TH CONFERENCE Book Series					
S128	Sarigiannis et al.	2014	Pneumologia Pediatrica					
S88	Schnell et al.	2012	Environmental Monitoring and Assessment					
WS29	Semple et al.,	2015	Tobaco control					
S109	Seto et al.	2009	Proceedings - 2009 IEEE International Symposium on Industrial Embedded Systems, SIES 2009					
S5	Sevin et al.	2016	Computers and Electrical Engineering					
S98	Shen et al.	2011	Integrating silicon nanowire field effect transistor, microfluidics and air sampling techniques for real-time monitoring biological aerosols					
WS62	Shin	2012	JOURNAL OF BIOMEDICINE AND BIOTECHNOLOGY					
S31	Sirbu et al	2015	PLoS ONE					
S13	Smith & Li	2016	International Symposium on Medical Information and Communication Technology, ISMICT					
S76	Steinle et al.	2013	Science of the Total Environment					
WS30	Steinle et al.,	2015	Science of total environment					
S100	The proceedings	2011	proceedings of the 8th International Scientific and Practical Conference on Environment, Technology and Resources					
S120	The proceedings	2007	Proceedings of the 14th International Union of Air Pollution Prevention and Environmental Protection Associations (IUAPPA) World Congress 2007, incorporating 18th Clean Air Society of Australia and New Zealand (CASANZ) Conference					
S73	The proceedings	2013	Applied Mechanics and Materials					
S66	The proceedings	2013	Advanced Materials Research					
S108	The proceedings	2009	IFMBE Proceedings					
S75	The proceedings	2013	Applied Mechanics and Materials					
S63	The proceedings	2014	Applied Mechanics and Materials					

S83	Uibel et al.	2012	Journal of Occupational Medicine and Toxicology					
S60	Uyanik et al	2014	Wireless Health 2014, WH 2014					
S54	Vagnoli et al	2014	IET Seminar Digest					
WS54	van der Schaaf et al	2013	ENVIRONMENTAL SOFTWARE SYSTEMS: FOSTERING INFORMATION SHARING Book Series					
WS67	Velasco et al	2007	ATMOSPHERIC CHEMISTRY AND PHYSICS					
S97	Wac et al.	2011	Proceedings of the 12th IFIP/IEEE International Symposium on Integrated Network Management, IM 2011					
S94	Wang et al.	2011	Proceedings of the 7th International Conference on Wireless Communications, Networking and Mobile Computing, WiCOM 2011					
WS50	Williams et al	2013	MEASUREMENT SCIENCE AND TECHNOLOGY					
S105	Wu et al.	2010	American Journal of Epidemiology					
WS55	Xiang et al	2013	9TH IEEE INTERNATIONAL CONFERENCE ON DISTRIBUTED COMPUTING IN SENSOR SYSTEMS					
WS15	Xiang et al	2016	14th Annual International Conference on Mobile Systems					
S113	Xu et al.	2009	IEEE Transactions on Biomedical Circuits and Systems					
S39	Yang	2015	Lecture Notes in Electrical Engineering					
S51	Yang et al.	2014	Journal of Medical Systems					
WS36	Yang et al.	2015	Proceeding of the 15th international conference on non-machine environment system engineering					
S21	Yang et al.	2016	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)					
WS18	Yang et al.	2016	14th International Conference on smart and health telematics					
S119	Yang et al.	2008	Journal of Natural Disasters					
S26	Yi et al	2015	Sensors (Switzerland)					
WS23	Ying et al.,	2015	Sensors					
S50	Zeiger & Huber	2014	IPSN 2014 - Proceedings of the 13th International Symposium on Information Processing in Sensor Networks (Part of CPS Week)					

S79	Zhao et al.	2013	Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference					
S111	Zou et al.	2009	Science of the Total Environment					
AD1	de Nazelle et al.	2013	Environmental Pollution					
AD2	Nyhan et al.	2014	Science of Total Environment					
AD3	Snik et al.	2014	Geophysical Research Letters					
AD4	Zwack et al.	2012	Atmospheric Environment					
AD5	Boogaard et al.	2009	Atmospheric Environment					
AD6	Thai et al.	2008	Science of Total Environment					
AD7	Dons et al.	2011	Atmospheric Environment					

6 Appendix B - PA studies exclusion/inclusion flow chart

Legend

- Scientific paper
- Conference proceeding
- Review paper
- Rejected during initial screening
- Rejected after full text reading

ID	Name	Year	Journal	Type of paper			Rejected	
				PAP	PRO	REW	Phase 1	Phase 2
WS48	Abdullah et al.	2012	TRENDS IN AUTOMOTIVE RESEARCH: Regional Conference on Automotive Research (ReCAR)					
WS60	Adams et al.	2009	JOURNAL OF ENVIRONMENTAL MONITORING					
WS33	Agir Berker et al.	2014	GEOINFORMATICA					
S49	Ahad et al.	2013	IFMBE Proceedings					
WS42	Aiello et al.	2012	COMPUTERS AND ELECTRONICS IN AGRICULTURE					
WS66	Allen et al.	2005	Photochemical & photobiological sciences					
PM3	Ancona et al.	2016	Annali dell'Istituto superiore di sanita					
WS54	Andersen et al.	2010	ANALYTICAL CHEMISTRY					
S77	Bell et al.	2009	8th European Conference on Noise Control 2009, EURONOISE 2009-Proceedings of the Institute of Acoustics					
S99	Bell et al.	2004	WIT Trasactions on the Built Environment					
S91	Belle et al.	2006	Proceedings of the 11th US/ North American Mine Ventilation Symposium					
WS10	BenZeev et al.	2016	PSYCHIATRIC SERVICES					
S107	Bernard et al.	1994	American Industrial Hygiene Association Journal					
S89	Buck et al.	2006	Record-IEEE PLANS, Position Location and Navigation Symposium					
S32	Buonanno et al.	2014	Science of Total Environment					
S103	Burch et al.	1999	American Journal Of Epidemiology					
S110	Burroughs et al.	1991	International Journal of Environmental Analytical Chemistry					
S14	Chatterjee et al.	2016	Proceedings of SPIE - The International Society for Optical Engineering					
WS43	Chen et al.	2012	ATMOSPHERIC ENVIRONMENT					
S102	Childers et al.	2000	Envronmental Health Perspectives					
WS19	Ciuzas et al.	2015	ATMOSPHERIC ENVIRONMENT					
PM19	Coca et al.	2010	Journal of occupational and environmental hygiene					
S48	Conti et al.	2013	IEEE Transactions on Instrumentation and Measurement					
PM13	Dario et al.	2012	La medicina del lavoro					

PM17	Dario et al.	2011	Giornale Italiano di medicina del lavoro ed ergonomia
WS2	Deary et al.	2016	AIR QUALITY ATMOSPHERE AND HEALTH
S56	Delgado-Saborit et al.	2012	Journal of Environmental Monitoring
S105	Diffey et al.	1995	Photochemistry and Photobiology
PM14	Elen et al.	2012	Sensors (Basel)
WS63	Elgethun et al.	2006	EPIDEMIOLOGY: ISEE/ISEA 2006 Conference
S42	Eto et al.	2013	Nihon eiseigaku zasshi. Japanese journal of hygiene
S37	Fabian et al.	2014	Fire Technology
S64	Fabian et al.	2011	Conference Proceedings-Fire and Materials 2011, 12th International Conference and Excibition
S62	Gaggioli et al	2012	Studies in Health Technology and Informatics
WS51	Gaggoli et al.	2012	ANNUAL REVIEW OF CYBERTHERAPY AND TELEMEDICINE 2012: ADVANCED TECHNOLOGIES IN THE BEHAVIORAL, SOCIAL AND NEUROSCIENCES
S4	Gall et al.	2016	Building and Environment
WS15	Gao et al.	2016	IEEE INFOCOM 2016 THE 35TH ANNUAL IEEE INTERNATIONAL CONFERENCE ON COMPUTER COMMUNICATIONS
S86	Gertman et al.	2007	IEEE Conference on Human Factors and Power Plants
S109	Glatkowski et al.	1993	Proceedings of SPIE
S5	Gourzoulidis et al.	2016	Physica Medica
S84	Green et al.	2008	Journal of the American Association for laboratory Animal science
S25	Hachem et al.	2015	SENSORNETS 2015 - 4th International Conference on Sensor Networks
S68	Hedgecock et al.	2010	Proceedings of the Annual southeast Conference
S69	Hodson et al.	2010	Nanotechnology: Bio Sensors, Instruments, Medical, Environment and Energy-Technical Proceedings of the 2010 NSTI Nanotechnology Conference
S8	Hu et al.	2016	PLoS ONE
S33	Hu et al.	2014	IEEE ISSNIP 2014
S30	Hu et al.	2014	ACM International Conference Proceeding Series
PM1	Huck et al.	2017	Environmental monitoring and assessment
S50	Hug et al.	2012	Proceedings of SPIE-The Intternational Society for Optical Engineering
WS49	Hug et al.	2012	ADVANCED ENVIRONMENTAL, CHEMICAL, AND BIOLOGICAL SENSING TECHNOLOGIES IX: Conference on Advanced Environmental, Chemical and Biological Sensing Technologies IX
S13	Hummel et al.	2016	ASTM Specail Technical Publication
S1	Ischer et al.	2017	Journal of Occupational and Environmental Hygiene
S59	Ismail et al.	2012	Applied Mechanics and Materials
S72	Ismail et al.	2010	American Journal of Applied Sciences
S71	Ismall et al.	2010	Journal of Applied Sciences

WS67	Jantunen et al.	2002	Chemosphere					
WS61	Kanjo et al.	2008	PERSONAL AND UBIQUITOUS COMPUTING					
S40	Kenny et al.	2014	2014 Science of Sport, Exercise and Physical Activity in the Tropics					
S43	Khasawneh et al.	2013	Nuclear Engineering and Design					
S16	Kim et al.	2015	Proceedings of the 1st ACM SIGSPATIAL International Workshop on the Use of GIS in Emergency Management					
WS59	Klepeis et al.	2009	ATMOSPHERIC ENVIRONMENT					
S98	Le Moullec et al.	2004	Petrole et Techniques					
S6	Lecoutere et al.	2016	IEEE Transactions on Biomedical Circuits and Systems					
WS38	Lee et al.	2013	20th IEEE International Conference on Image Processing					
S38	Lim et al.	2014	Biotechnology and Biotechnological Equipment					
S111	Loh et al.	2017	International Journal of Environmental Research and Public Health					
S20	Lu et al.	2015	ISPRS International Journal of Geo-Information					
WS55	Mahyuddin et al.	2010	BUILDING AND ENVIRONMENT: 11h International Conference on Air Distribution in Rooms (ROOMVENT 2009)					
S11	Marek et al.	2016	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives					
S27	Markvart et al.	2015	LEUKOS - Journal of Illuminating Engineering Society of North America					
S88	Martinez et al.	2007	5th US Combustion Meeting					
S60	Michelsburg et al.	2012	Proceedings of SPIE-The International Society for Optical Engineering					
WS50	Michelsburg et al.	2012	MULTIMEDIA ON MOBILE DEVICES 2012 AND MULTIMEDIA CONTENT ACCESS: ALGORITHMS AND SYSTEMS VI: Conference on Multimedia on Mobile Devices and Multimedia Content Access Algorithms and Systems VI					
WS56	Miller et al.	2010	LIGHTING RESEARCH & TECHNOLOGY					
S87	Milton et al.	2007	Environmental Monitoring and assessment					
S85	Mittra et al.	2007	IETE Journal of Reserach					
S90	Moere et al.	2006	ACM International Conference Proceeding Series					
WS17	Moore Elizabeth et al.	2016	BMJ OPEN					
S108	Moschandreas et al.	1994	Journal of Exposure Analysis and Environmental Epidemiology					
S78	Mun et al.	2009	MobiSys09-Proceedings of the 7th ACM International Conference on Mobile systems, Applications, and Services					
WS14	Munoz et al.	2016	2016 IEEE 18TH INTERNATIONAL CONFERENCE ON EHEALTH NETWORKING, APPLICATIONS AND SERVICES (HEALTHCOM)					
S46	Nash et al.	2013	Proceedings of SPIE The International Society for Optical Engineering					
WS53	Negi et al.	2011	JOURNAL OF EXPOSURE SCIENCE AND ENVIRONMENTAL EPIDEMIOLOGY					
S23	Nieuwenhuijsen et al.	2015	Environmental Science and Technology					

S31	Nieuwenhuijsen et al.	2014	International Journal of Environmental Research and Public Health					
S12	Nieuwenhuijsen et al.	2016	Environmental Health: A Global Access Science Source					
S92	No author name available	2006	Environmental Health Perspective					
S61	No author name available	2012	Biomedical Wireless Technologies, Networks, and Sensing Systems, BioWireleSS					
S17	Noe et al.	2015	1st URSI Atlantic Radio Science Conference, URSI AT-RASC 2015,					
S66	Nuawi, M.Z., et al.	2011	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS					
S24	Patsakis et al.	2015	Lecture Notes in Computer Science					
S22	Pilla et al.	2015	Sustainable Cities and Society					
WS37	Predic et al.	2013	IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)					
S3	Rabinovitch et al.	2016	Environmental Health: A Global Access Science Source					
WS5	Read et al.	2016	OPTOMETRY AND VISION SCIENCE					
S81	Reddy et al.	2008	Proceedings-International Symposium on wearable Computors, ISWC					
S76	Rehman et al.	2009	SoCPaR 2009-Soft Computing and Pattern Recognition					
WS18	Reis et al.	2015	ENVIRONMENTAL MODELLING & SOFTWARE					
S74	Riva et al.	2010	Cyberpsychology, behaviour and social networking					
PM12	Rodes et al.	2012	Atmospheric environment					
S29	Rogers et al.	2015	Proceedings of SPIE - The International Society for Optical Engineering					
PM10	Ryan et al.	2015	The science of the total environment					
S63	Sakamoto et al.	2012	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences-ISPRS					
S112	Sarigiannis et al.	2017	Pneumologia Pediatrica					
S67	Sarma et al.	2011	Biochip Journal					
S57	Schnell et al	2012	Environmental Monitoring and assessment					
S79	Seto et al.	2009	Proceedings-2009 IEEE International Symposium on Industrial Embedded Systems, SIES 2009					
S2	Seyam et al.	2016	Proceedings - Frontiers in Education Conference, FIE					
S28	Sheridan et al.	2015	Proceedings of SPIE - The International Society for Optical Engineering					
S45	Šindelar et al.	2013	2013 Proceedings of SPIE The International Society for Optical					
S101	Soehren et al.	2002	Record-IEEE PLANS, Position Location and Navigation Symposium					
S39	Steele et al.	2014	ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE)					
WS25	Steele et al.	2015	PROCEEDINGS OF THE ASME INTERNATIONAL MECHANICAL ENGINEERING CONGRESS AND EXPOSITION, 2014, VOL 4A					
PM15	Steinle et al.	2013	The science of the total environment					
WS24	Steinle et al.	2015	SCIENCE OF THE TOTAL ENVIRONMENT					

S19	Sun et al.	2015	Journal of Medical Engineering and Technology					
S97	Sung et al.	2004	Proceedings-International Symposium on Wearable Computers					
S104	Svirchev et al.	1999	Pulp and Paper Camada					
S94	Tapiu et al.	2006	Lecture Notes in Computer Sciences					
S106	Toghiani et al.	1995	ISA TECH/EXPO Technology Update Confrence Proceeding					
S36	Turner et al.	2014	2014 IEEE Transactions on Geoscience and Remote Sensing					
WS64	Uenoyama et al.	2006	MEDICAL & BIOLOGICAL ENGINEERING & COMPUTING					
S26	Uyanik and Dursun	2015	SPE Annual Technical Conference and Exhibition					
S83	Van Gelder et al.	2008	Prehospital Emergency care					
WS4	Velasco et al.	2016	ATMOSPHERIC ENVIRONMENT					
S75	Vogt et al.	2010	Journal of the Southern African Institute of Mining and Metallurgy					
S9	Volckens et al.	2016	Indoor Air					
S35	Vrijhejd et al.	2014	Thorax					
S10	Walczykowski et al.	2016	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives					
S51	Walter and Mayer	2012	IEMSs-Managing Resources of a Limited Planet: Proceeding of the 6th Biennial Meeting of the International Environmental Modeling and Software society					
S18	Wasisto et al.	2015	Microelectronic Engineering					
PM20	Wenger et al.	2005	Journal of agricultural safety and health					
WS65	Wiest et al.	2006	ANALYTICAL LETTERS: 2nd International Workshop on Biosensors for Food Safety and Environmental Monitoring					
S73	Wu et al.	2010	American Journal of Epidemiology					
WS41	Wu et al.	2012	ENVIRONMENTAL HEALTH					
WS46	Yueh et al.	2012	PLOS ONE					
S15	Zaidner et al.	2016	biosystems Engineering					
WS47	Zaunmayr et al.	2012	Conference on Health Informatics Meets eHealth from Science to Practice and Back Again Mobile Health and Care Preventive Health Care Always and Everywhere (eHealth)					
S93	Zhao et al.	2006	Internatioal Journal of Pattern Recognition and Artificial Intelligence					

7 Appendix C - List of relevant EU projects

Project	Focus	Outcome relevant for defining external exposure at individual level within ICARUS
INTASENSE	The INTASENSE concept is to integrate a number of micro- and nano-sensing technologies onto a common detection platform to produce a low-cost miniaturised system that can comprehensively measure air quality, and identify the nature and form of pollutants. http://www.intasense.eu/	The INTASENSE air quality monitor wirelessly linked to air-handling and pre-conditioning infrastructure allowing air circulation to be managed in an energy efficient way while maintaining a healthy environment. Sensors developed within the project: PM, ozone, SO2, NO_2, VOCs, CO and CO_2 - conductometric type sensors for combustion gas and VOC - particle detection by a particle-induced discharge
EO2HEAVEN	EO2HEAVEN 'Earth observation and environmental modelling for the mitigation of health risks' advanced knowledge on the impact of environmental factors on public health outcomes. Project focused on the effect of atmospheric pollution on cardiovascular and respiratory diseases. http://www.copernicus.eu/projects/eo2heaven	EO2HEAVEN has developed methodologies, correlation models, spatial data services (using Standards of the Open Geospatial Consortium) and applications supporting the main activities involved in environmental health: • discovery and acquisition of environmental data • integration of heterogeneous Earth observations (satellite, in-situ and field data) • extraction of time series and visualization of graphs and maps • development of models of health effects • development of risk maps • development of predictions for early warning systems
CITI-SENSE	The CITI-SENSE project developed and tested components of environmental monitoring and information systems based on innovative and novel Earth Observation capabilities. The applications focused on the citizens' immediate environment regarding urban air quality, environmental quality of urban public spaces and indoor air quality in schools. http://www.citi-sense.eu/	Personal Air Monitoring Toolkit (Little Environmental Observatory – LEO) was developed that allows users to assess air quality in their immediate surroundings. It is based on a sensor device that monitors three gases using electrochemical sensors from Alphasense (nitrogen dioxide, nitrogen monoxide and ozone) and a corresponding mobile application (ExpoApp). The users can acess their individual information in real time via app or from the CITI-SENSE platform.
AirMonTech	AirMonTech is an EU FP7 project compiling knowledge and information needed to harmonize air pollution measurements now, and to guide decisions about monitoring technologies and strategies in the future. http://www.airmontech.eu/	One of the recommendations resulting from AirMonTech on future urban air quality monitoring and strategy is the following: Low cost gas sensors, such as those based on electrochemistry, have a large potential for enabling high spatial density monitoring which would be beneficial in urban areas. However, there is currently only preliminary evidence of their real world performance in terms of, for example, specificity and stability the most promising evidence being for ozone sensors.
EXPOSOMIC	EXPOSOMICS (Enhanced exposure assessment and omic profiling for high priority environmental exposures in Europe) aimed to predict individual disease risk related to	Personal exposure monitoring (PEM) of PM2.5 and ultra-fine particle (UFP), allowed insight into micro-environmental (home, travel by mode, work etc.) contributions to exposures. TSI Condensation Particle Counter 3007 model was used.

	the environment, by characterizing the external and internal exposome for common exposures (air and drinking water contaminants) during critical periods of life, including in utero. http://www.exposomicsproject.eu/	
SENSINDOOR	SENSINDOOR (Nanotechnology based intelligent multi-SENsor System with selective pre-concentration for Indoor air quality control) aimed at development of novel sensor systems for extremely sensitive, highly selective and long-term stable operation were studied and developed for advanced control of Indoor Air Quality. http://sensindoor.eu/	Nanotechnology-based microsystem for selective monitoring of hazardous VOCs was developed that can detect hazardous VOCs, primarily benzene, formaldehyde and naphthalene at parts per billion (ppb) concentration levels in indoor air selectively against a complex background of other organic and inorganic gases.
IAQSENSE	IAQSENSE (Nanotechnology based gas multispectral sensing system for environmental control and protection) objectives were to develop sensor systems for VOC, including all electronics, pattern detection firmware and validate these systems and their impact in real environments, firstly in buildings, but also show the potential in vehicles and for health and hazard scenarios. http://cordis.europa.eu/result/rcn/173496_en.html	VOC indoors: the main technology innovation is based on surface ion mobility dynamics, it separates each gas component and its concentration like a mass spectrometer and allows high sensitivity (ppb) fast (1s) multi-gas detection.
PEOPLE	The PEOPLE project (Population Exposure to Air Pollutants in Europe) has been assessing outdoor, indoor and personal exposure levels of air pollutants in European cities, focusing on emissions from transport and smoking. http://ies.jrc.ec.europa.eu/people-project	Citizens carried diffusive sensor for benzene for 12 hours to measure their personal exposure to the pollutant. It was possible to establish the influence of the variables considered in the personal exposure model in relative terms.
CETIEB	CETIEB (Cost-Effective Tools for Better Indoor Environment in Retrofitted Energy Efficient Buildings) objective was to develop innovative solutions for better monitoring the indoor environment quality and to investigate active and passive systems for improving it. http://www.cetieb.eu/SitePages/Home.aspx	Advanced IR spectrometric VOC sensor for indoor air that can detect volatile organic compounds (VOCs) to the level of 2ppm. While not as sensitive as the existing Total VOC MOX sensor arrays, the new sensor has the advantage of using the spectrum to easily distinguish between different substances. It is composed of microspectrometre which is based on a detector with an integrated MEMS (Microelectromechanical system) Fabry-Pérot filter on a chip.

Plume Air Cloud	Plume Air Cloud (Air Quality Data Crowdsourcing Platform for Environmentally-friendly Cities) aimed at helping consumers track and reduce the impact of air quality on their health and well-being, and supporting policymakers in promoting smarter mobility choices to build cleaner cities. http://cordis.europa.eu/project/rcn/212231_en.html	Flow, a portable, AI-equipped air quality tracker is used to measure PM 2.5, NO_2, O_3, VOC, T and RH in the area immediately around a user.
ISCAPE	ISCAPE (Improving the Smart Control of Air Pollution in Europe) aims to integrate and advance the control of air quality and carbon emissions in European cities in the context of climate change through the development of sustainable and passive air pollution remediation strategies, policy interventions and behavioural change initiatives. https://www.iscapeproject.eu/	Through the approach of Living Labs the team will deploy a network of air quality and meteorological sensors (both stationary and mobile) and evaluate through analysis and a suite of up-to-date numerical modelling the benefits expected from the interventions on a neighbourhood and city-wide scale for several aspects ranging from quantification of pollutant concentration to exposure. iSCAPE encapsulates the concept of "smart cities" by promoting the use of low-cost sensors, engaging citizens in the use of alternative solution processes to environmental problems.
EVERYAWARE	EVERYWARE (Enchance Environemntal Awarness through Social Information Technologies) project intended to integrate all crucial phases (environmental monitoring, awareness enhancement, behavioural change) in the management of the environment in a unified framework, by creating a new technological platform combining sensing technologies, networking applications and data-processing.tools http://www.everyaware.eu/	Embraced the challenge of helping people to work out exposure to air pollution and make informed choices regarding the best times to be out and about, all this with a cheap, reliable and easy to use equipment. SensorBox, a portable device that measures concentrations of pollutants in the air (CO, NO2, O_3, VOC) and localize them through a GPS was developed. All the software and the hardware developed in the framework of the EveryAware project are open and available for download.