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# Use Case of Building an Indoor Air Quality Monitoring System

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***Abstract*— On average, we spend around 90% of the time in indoor environments. Indoor Air Quality (IAQ) has been receiving increased attention from the environmental bodies, local authorities and citizens as it is becoming clearer that poor IAQ has public health implications. Therefore, monitoring of indoor environment and involving citizens becomes crucial to enhance IAQ and managing their indoor environments by raising awareness – a goal of many Citizen Science (CS) projects. In this work, we present a use case of IAQ monitoring in a European project with a focus on Smart Cities with citizen engagement and involvement. It is well known that the cost of Air Quality (AQ) monitoring stations, which are often stationary, and generally produce reliable, and high-quality data is a non-starter for CS projects as cost prohibits the scaling of deployment and citizen involvement. On the other hand, it is widely assumed that low-cost devices for AQ, although available in abundance, often produce low-quality data, putting the credibility of basing any analysis on low-cost sensors. There is an increasing number of research efforts that look at how to ascertain the data quality of such sensors so that they could still be used reliably, often to provide indicative readings, and for analytics. In this work, we present data science-based techniques that have been utilised for selecting low-cost sensors based on their data quality indicators, and an integrated visualisation system that utilises structure data for IAQ to support multi-city trials in a CS project. The sensors are selected after analysing their consistency over a period by applying different approaches such as statistical analysis and graphical plots.***

***Keywords*— air pollution, indoor air quality, IoT, low-cost sensors, knowledge graph, citizen science**

## I. Introduction

Good air quality is a major concern globally mainly in urban areas where vehicle traffic and industries are bringing air pollution which directly affects human health [1]. Air pollution is mainly categorised into two segments: ambient (outdoor) and indoor air pollution. IAQ is receiving increasing attention in the last few years from the environment authorities, political institutes, and the scientific community. The use of coal, wood, stove or other energy sources for cooking and heating inside their houses is a common practice [2]. The combustion from such sources generates heat, light along with carbon dioxide ($CO_2$) and particulate matters ($PM_{2.5}$ & $PM_{10}$). In addition, some of the impurities in the fuel generate by-products such as Nitrogen dioxide ($NO_2$), Sulphur oxides ($SO_x$), Carbon monoxide (CO) and unburned hydrocarbons. Besides these, anthropogenic sources (building materials, paints) or biomass fuel burning into houses also generate pollutants such as Volatile Organic Compounds (VOCs) and radon which also contributes to indoor air pollution [3].

Often it is perceived that indoor air quality fares better in comparison to the ambient air quality, but several studies [4, 5] show that indoor air pollution is two to five times worse than outdoor pollution which raises a concern on human health in indoor environments. Additionally, air pollution is a major driver in health inequality - it disproportionately affects children, poorer households, older people and people with pre-existing conditions [6]. Whilst focus remains on outdoor pollution, people typically spend over 90% of their daily time indoors where levels of pollution often surpass outdoor environments [2, 7]. The increased importance of measuring IAQ has lead to gradual growth in approaches for IAQ monitoring using the Internet of Things (IoT) devices. These devices measure various gases and particulate matters in indoor environments and are connected with the internet to transmit measurements for analytics which helps in monitoring and analysis of the indoor environment and hence building a dense IAQ monitoring network [8]. Involvement of citizens in taking part in such sensor design and monitoring is crucial – and a key component of CS projects [9-11].

Engagement of citizens in monitoring any system time and again comes with the question "What does the measurement mean to the citizens? However, this question allows engaging citizens to clarify the importance of the IAQ monitoring, motivate and engage them in monitoring the process [12]. To generate the awareness at citizen's level, apart from volunteer participation and data gathering, inclusion, collaboration and reciprocation is required [13]. In other words, a communication bridge is required between concerned authorities and citizens to engage citizens in air quality monitoring and hence raise awareness. This reflects the need for developing IAQ monitoring platforms that increase the citizens' understanding and awareness of indoor air pollution and act as a communication bridge.

However, monitoring indoor air pollution at the household level in CS projects is challenging as such monitoring tools are not accessible to citizens at the territory level as the high-quality certified equipment is extremely costly. Instead, they have been deployed as static monitoring stations across cities worldwide to monitor outdoor air pollutions. These costly and more reliable devices often cost many times higher than the cost of low-cost devices – making it infeasible to scale the measurement at the indoor level [14]. The low-cost devices allow creating affordable IAQ monitoring platform at citizens' level to make them able to related IAQ and their activities. Besides, it has been also argued that IAQ data from different areas can help local stakeholders to manage air quality and associated risk in those areas [13]. It is widely accepted that there is a trade-off between using high cost and generally high-fidelity devices, against low cost and often low fidelity devices when scaling up air quality monitoring. Hence, data quality is a major challenge while collecting and interpreting data using low-cost devices and they are often utilised in limited settings to deliver relative and aggregated knowledge on IAQ [14]. In this paper, we present a use case of dealing with IAQ monitoring in the context of a European project in urban settings – and set out our experience of developing: a) low-cost sensor kits for measuring different gases and particulate matters that are relevant in IAQ context b) use of data science to ascertain data quality to be able to choose between different sensor options to design the final kit c) an AI data platform utilising knowledge graphs that offers structured data that facilitates interactive visualisation of the IAQ data. As per our research, our work is first to offer such use cases to help other projects and efforts in this increasingly important area of research.

In the rest of the paper, related work is presented in Section-II. The system architecture of Indoor Air Quality Monitoring, Kit design and experimental work is presented in Section-III. Discussion and conclusion with the future works are presented in Section-IV.

## II. Related work

Air pollution is getting more attention in recent years as its direct impact on health is becoming clearer [6]. According to the report published by WHO in 2012, 11.6% of all global deaths were caused by air pollution [15]. Some of the common health issues such as cardiovascular disease, respiratory conditions and in some cases cancer are also associated with air pollution [16]. Centre for Cities' annual study released that an estimated 4.3% of deaths (2017) in Bradford - a city in North of England and the focus of this work, can be attributed to long-term exposure to $PM_{2.5}$ [17]. IAQ – the focus of recent work in the AQ research field, is still relatively little understood in terms of the interface between indoor and outdoor air quality, and how ambient air quality impacts the quality of air in households [18]. One of the key challenges from a technology perspective in the IAQ domain is to design IAQ monitoring systems using real-time monitoring of gases and particulate matters specific to IAQ and common with Outdoor Air Quality (OAQ). Citizen's involvement in IAQ monitoring using CS methodologies is paramount due to the nature of work required to make such monitoring effective – as it has to be done in situ in households [19]. The conventional high-cost air monitoring systems are not practically suitable to monitor indoor environment because of their size, cost, installation complexity, complicated functioning and skill set is required to handle such systems [7].

Instead, in recent years, the Internet of Things (IoT) technology and Single Board Computers (CBC) are commonly used to monitor air quality using various low-cost sensors [8]. Krystallia et al. [20] examine the IAQ of three schools for two seasons and found that ambient air through ventilation of rooms and seasons have significant effects on indoor air pollutants and student's health. A similar study conducted by Corinne et al.[21] for two seasons (summer and winter) at 37 office buildings in 8 European countries shows that the concentrations of some pollutants like aldehydes and $O_3$ are higher in summer while $NO_2$ and benzene are higher in winter. The study conducted by Wenjuan et al. [22] for green building certifications for 30 countries worldwide shows that ventilation, emission source control of pollutants and indoor air measurements are the key components to certify and manage indoor air quality. A real-time case study conducted by Chakraborty et al. [23] on residential stove usage inside 20 houses in Sheffield (UK) shows that $PM_{2.5}$ and $PM_{10}$ concentration values are much higher when citizen burn wood in their houses as compared to the non-stove user. Also, it compares the outdoor air quality with indoor at the same time and results showed that these pollutants are mainly originated from indoor substances. Semmens et al. [24] monitor $PM_{2.5}$ and Particle Number Concentrations in 96 households in the United States where wood stoves are the primary source for heating. The results showed that the mean $PM_{2.5}$ level exceeds WHO air quality guidelines.

Though air pollution directly affects citizens' health, there has been less awareness among citizens because of the complexity in monitoring and interpreting the pollution data within their home environments [25]. Mahajan et al. [13] stated that the inclusion of citizens can benefit from generating community-led air quality monitoring awareness. Their study also presented that enhance citizens' knowledge of air pollution can reduce individual exposure level to pollution and hence tackle the pollution problem at the community level. Hubbell et al. [26] have presented the conceptual framework to guide the citizens and other stakeholders on the use of low-cost sensor devices system. The framework has presented focusing on how the implementation of low-cost sensors, communication of data and response can establish a relationship between citizens and air quality monitoring stakeholders to understand the poor air quality risk and improve air quality. Tiele et al. [27] have presented a low-cost sensor-based indoor real-time monitoring system towards citizens' engagement in indoor air quality where researchers and interested citizens have been participated to improve the indoor environment by experimenting the IAQ monitoring system in different close environment.

The IoT-based monitoring system uses wireless sensor network architecture for communication and sends data to the remote server or any other monitoring platform such as the mobile app, web interface once the device monitor the data [28]. Building such a system, Salman et al. [29] presented a real-time indoor air quality monitoring system with a wireless sensor network to visualize the measured pollutants data from the indoor environment. In a similar kind of work, Fang et al. [30] developed a home-based IoT monitoring platform that can detect indoor pollution along with forecasting the pollution level and suggestions to improve the air quality. These related works in the area of IAQ highlighted that there is a need for an integrated system, with accessible low-cost sensors. However, it is challenging to utilize low-cost sensors as often they lack credibility in terms of sensing data quality. At the same time, CS projects that really can give impetus to one of the most important subjects of this generation can only work if the cost of devices is lower and scalable. Strategic selection of low-cost sensors that are reliable and can provide indicative results is a relatively new area of research and there is very limited work in this area so far. We present one such approach with the use of data science techniques to allow selecting sensors from multiple options in the market for IAQ monitoring and present our experience and findings in a real-world use case. This real-world use case is applied in a large European project on Smart Cities and Open Data Reuse (SCORE), where a multi-site trial of IAQ monitoring is planned. We also present a system architecture and implementation of a system that is unique in terms of the use of data structure. Data is stored in the form of Knowledge Graphs that has the potential for better search and visualization. In doing so, the first usable Ontology – a knowledge structure required to build Knowledge Graphs is presented – which has the potential to be reused in other AQ monitoring projects.

## III. Indoor Air Quality Monitoring: System Architecture

The implementation of the proposed IAQ monitoring system is developed with the system architecture as shown in Figure 1.


Figure 1: Indoor Air Quality Monitoring: System Architecture

This system architecture mainly has three components: i. IAQ Sensors, ii. Knowledge Graph and iii. Data Visualisation Platform.

### IAQ Sensors

An indoor environment is any enclosed premises such as a house, office, school or university where citizens spend a significant amount of time. The indoor environment may contain different appliances, domestic products which may act as a source for air pollutants, mainly PM and different gases. Several pollutants such as PM, $CO_2$, NOx, $O_3$, $SO_2$, radon, volatile and semi-volatile organic compounds (VOCs) and microorganism have recognised as indoor pollutants. Among these, some of the pollutants, PM, $CO_2$, NOx, $O_3$, $SO_2$ are common in both indoor and outdoor environment [3, 7, 31]. Pollutants such as $CO_2$, PM are heavily dependent on indoor activities like cooking, heating whereas pollutants for example VOCs, CO has appeared mainly from outdoor sources. There appears that the types of indoor pollutants and their sources are different from outdoor [3].

To measure these pollutants, in this work following candidate sensors have been considered. This selection of sensors is based on other studies and experiments [23, 32-34].

- BME680: This sensor is used to measure temperature, humidity, barometric pressure and VOC gas.
- CJMCU-811: This sensor is used for detecting $eCO_2$, VOC gases. It is a digital gas sensor integrated CCS801 sensor and 8-bit Analog-to-digital converter (ADC).
- Envrio+: This pHAT is a collection of multiple sensors such as BME280 which measures temperature, humidity and pressure, MICS6814 analogue gas sensor is responsible to measure CO, $NO_2$ and Ammonia (NH3) and LTR-559 light and proximity sensor. Also, it has a built-in ADS1015 analogue-to-digital convertor and 0.96" colour LCD (160 × 80) for display.
- SDS011: This sensor is used to measure $PM_{2.5}$ and $PM_{10}$ air pollutants. This sensor is an infrared-based laser sensor and has a fan to provide self-airflow
- MQ-2: This gas sensor is mainly used to detect CO, Methane, Butane, LPG, smoke.
- PMS5003: It is used to measured $PM_1$, $PM_{2.5}$ and $PM_{10}$.
- OPC-R1: This sensor is used to detect $PM_1$, $PM_{2.5}$ and $PM_{10}$ with the help of laser scattering technology.
- SGP-30: This gas sensor is mainly used to monitor $eCO_2$ and TVOC.

Low-cost sensors selection that is reliable is a major challenge in building any AQ monitoring system. In order to select sensors among the competing sensors in particular for measuring PM variants, three sensors (SDS011, PMS5003 and OPC-R1) have been deployed in a controlled lab environment (no human or any other mobility within the environment) for 48 hours with reading interval every 15 minutes. From the plot, it can be observed that these sensors have different patterns of readings for $PM_{2.5}$and $PM_{10}$. Since there has been no external interference to the measuring environment, it is expected that the pollutant reading should not vary in the wider range. From the observation, among three sensors, it has been analysed that the SDS011 sensor has a lower variance. In other words, SDS011 has shown a higher linearity pattern in comparison to the other two sensors in the controlled lab environment as can be observed in Figure 2 for $PM_{2.5}$ and Figure 3 for $PM_{10}$.

After analysing the graphical plot, we also applied statistical measures to validate the consistency of sensors to bring further confidence in the selection of the sensor. For the statistical analysis, first of all, the density distribution of these three sensors readings has been analysed, as listed in Table I for $PM_{2.5}$ and Table II for $PM_{10}$

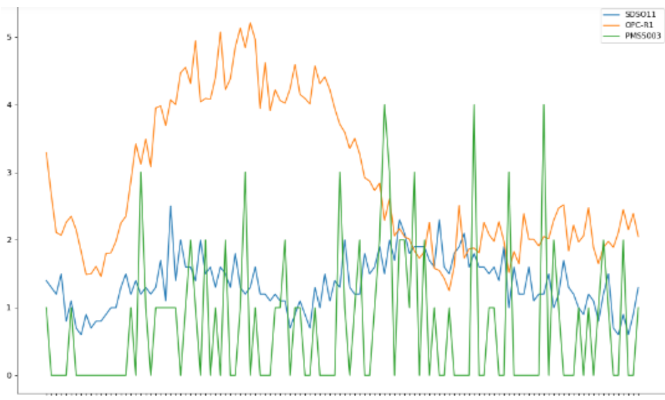


Figure 2: Comparison plot of PM sensors (SDS011: Blue, OPC-R1: Orange and PMS5003: Green) in a controlled lab environment (no human or any other mobility within the environment) for $PM_{2.5}$ for 48 hours where the linearity of the plot is analysed as one of the sensor selection criteria.

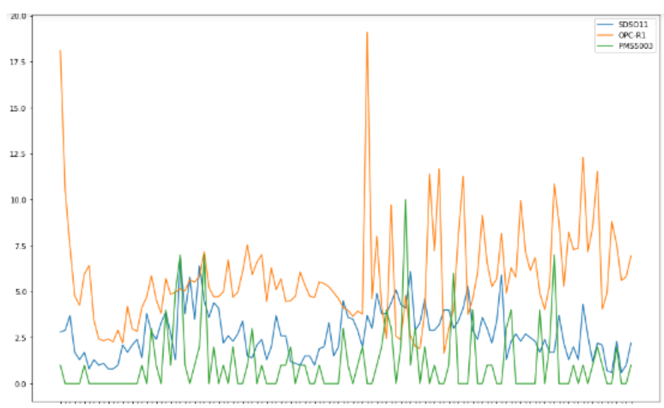


Figure 3: Comparison plot of PM sensors (SDS011: Blue, OPC-R1: Orange and PMS5003: Green) in a controlled lab environment (no human or any other mobility within the environment) for $PM_{10}$ for 48 hours where the linearity of the plot is analysed as one of the sensors selections criteria.

TABLE I. STATISTICAL OBSERVATION OF $PM_{2.5}$ FROM THREE SENSORS

| | **Name of the PM sensors** | | |
|---|---|---|---|
| | ***SDS011*** | ***OPC-R1*** | ***PMS5003*** |
| Number of Observations | 96 | 96 | 96 |
| Mean | 1.358 | 2.871 | 0.725 |
| Standard Deviation | 0.394 | 1.108 | 1.003 |
| Minimum Value | 0.6 | 1.25 | 0.0 |
| Maximum Value | 2.5 | 5.21 | 4.0 |
| 90% distribution value | 1.9 | 4.41 | 2.0 |

TABLE II. STATISTICAL OBSERVATION OF $PM_{10}$ FROM THREE SENSORS

| | **Name of the sensor** | | |
|---|---|---|---|
| | ***SDS011*** | ***OPC-R1*** | ***PMS5003*** |
| Number of Observations | 96 | 96 | 96 |
| Mean | 2.709 | 5.809 | 1.083 |
| Standard Deviation | 1.33 | 2.802 | 1.77 |
| Minimum Value | 0.6 | 1.64 | 0.00 |
| Maximum Value | 6.8 | 19.1 | 10.0 |
| 90% distribution value | 4.4 | 8.853 | 3.00 |

From Table I & II, it can be observed that SDS011 has the lowest Standard Deviation (SD) for both $PM_{2.5}$ and $PM_{10}$ readings. This lower SD value implies that the readings are more uniformly distributed. In the controlled environment, readings are expected to have the least possible SD. The SD value also reflected that SDS011 has better performance than the other two sensors during the lab environment experimentation. In further analysis, 90% of distributed values has been inspected for each sensor to find the deviation value from the mean value. The observation shows that the SDS011 sensor has the minimum deviation from the mean value, for both $PM_{2.5}$ and $PM_{10}$. In the further evaluation for sensor selection, the drift has been analysed as it is being used to identify the general trends in the data distribution [35]. For the drift calculation, two SDS011sensors and two PMS5003 sensors are deployed in the same lab environment for 48 hours. The recorded data from one SDS011 sensor is compared to another SDS011 and the PMS5003 sensor is compared to another PMS5003 to analyze the drift between the two data sets. In general, data from the same environment recorded by two same sensors should have the minimum drift. To analyse the drift, the Kolmogorov-Smirnov (KS) algorithm [36] has been applied that calculate the drift value for both setup sensor data. From the statistical analysis, as listed in Table III, it is observed that SDS011 sensors are more consistent for both $PM_{2.5}$ and $PM_{10}$, with each other in the same environment as compare to the PMS5003. From these analyses, it has been analysed that the SDS011 shows the best performance among the three PM sensors. These approaches that have applied to selected the sensor for measuring PM guide to select the other best viable sensors among different low-cost sensor options to measure other pollutants in the IAQ monitoring system.

TABLE III. KS-STATISTICAL COMPARISON FOR DRIFT ANALYSIS

| | **Name of the sensor** | |
|---|---|---|
| | ***SDS011*** | ***PMS5003*** |
| $PM_{2.5}$ (KS-Statistics) | 0.2163 | 0.2339 |
| $PM_{10}$ (KS-Statistics) | 0.1929 | 0.2397 |

After the section of sensors, the kit has been assembled as shown in Figure 4 that contains BME680, CJMCU-811, Enviro+, MQ-2 and SDS011 sensors. The deployable IAQ kit is a combination of these multiple sensors and Raspberry Pi 3B+ - which controls the whole sensor kit. The Raspberry Pi have features like Bluetooth, 4 USB ports, a Micro SD port for storage and access, a wireless LAN, and 28 GPIO pins for external communication. All the sensors are connected with raspberry pi with the help of a GPIO pin expander, which is mounted on it, however, the PM sensor is connected through the USB port with UART output. The connected sensors sense and detect species from the indoor environment and generate analogue/digital signals and hence pass to raspberry pi for further process. A built-in Wi-Fi adapter helps raspberry pi to establish access to the internet and start detecting sensors' data and send the data to the web server.

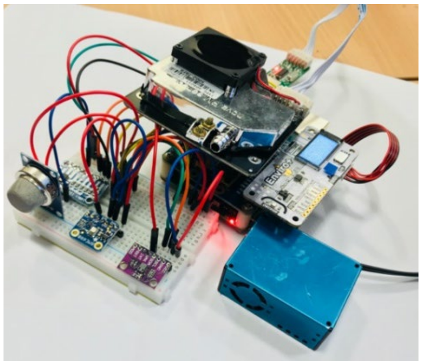

Figure 4: Final Sensor kit with IAQ sensors using Pi 3B+

### Knowledge Graph

Data from the sensor kits are received and parsed using RESTful Application Program Interface (API) before storing it into the data store. In our web service, the RESTful API, using an HTTP request, has been created using Python and the Flask web framework to communicate between different nodes of the system. Data is streamed from the sensor kits and is stored in a Triple store [37] in the form of a Knowledge Graph (KG) [38]. An ontology for Air Pollution has been developed that is required to give structure to the KG. Figure 6 shows the graphical representation of the pollution ontology.

The knowledge graph provides the framework for data integration, unification and data linking. This ontology is released as open-source and made available for other AQ monitoring projects here[1].

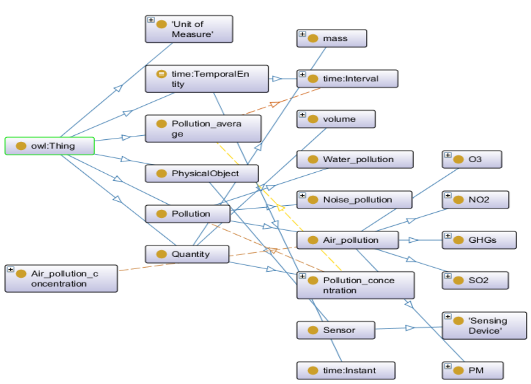


Figure 6: Graphical Representation of the Pollution Ontology – highlighting Indoor Air pollution branch structure.

### Data Visualisation Platform

The data visualization platform provides the interface which allows citizens or end-users to observe the measured data in an interactive manner such as the selection of locations, filtering different data, plotting and alert generation without any programming skills. For the data visualization, a web application using PHP, HTML and JavaScript has been created. In the web application, the user can see the approximate sensor locations (instead of absolute locations to preserve privacy) and can choose any pollutant or all of the pollutants to visualise the measured level as per the specified period such as 1 day, 1 week or 1 month. This platform provides an interactive visualisation such as selecting multiple pollutants together or altering them in visualisation, downloading the selected data, comparing them with threshold values and hence the colour coding on the visualisation. Figure 7.a, 7.b and 7.c reflect the web application visualisation platform of the different web pages such as a Home page with selection fields (Figure 7.a), sample plot for $PM_{2.5}$ for 1-Day (Figure 7.b) and the informative page (Figure 7.b).

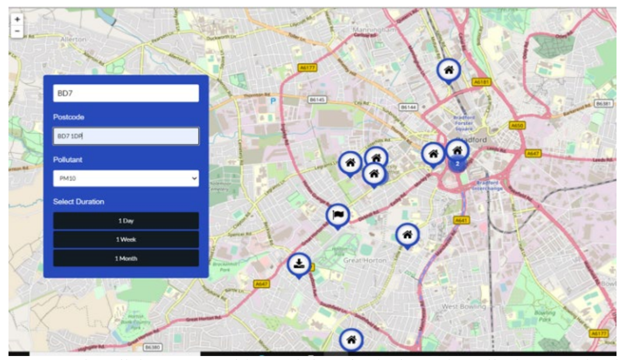


Figure 7.a: Visualising Sensor kits and data for indoor air pollution monitoring at one of the city sites in the SCORE project. Citizens can search based on postcode and it will show IAQ devices in the searched geographic location.

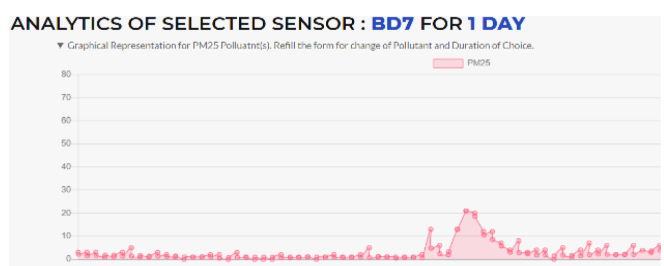


Figure 7.b: Visualising 1-Day time series plot of PM2.5 with varying reading with upper range 20 µg/m3, which below the WHO upper limit.

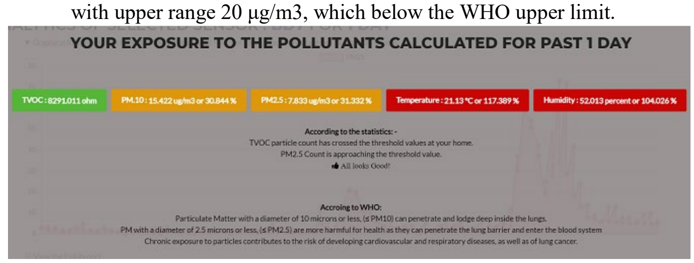


Figure 7.c: Visualisation system used by a Citizen shows them a summary of the pollutants in their homes and gives information on what the summary means and steps they can take to improve IAQ.

[1] http://212.48.88.88/score/ontologies/

## IV. Discussion & Conclusion

IAQ monitoring is one of the growing concerns in recent years because of its impact on human's day-to-day life along with direct implication on health. However, interactive, and informative IAQ monitoring that can engage citizens is still not commonplace largely due to the cost-prohibitive monitoring devices and also the low confidence in data quality of the low-cost devices. This hampers CS science efforts that can scale indoor air quality monitoring effort and bring much-needed impetus to this all-important area. In this work, an IAQ monitoring system is implemented where the strategies on the selection of low-cost sensors based on statistical methods and Knowledge Graph with associated knowledge structure have been presented. The system produces an interactive visualisation platform to inform citizens about IAQ in their neighbourhood and in their houses including analytics on average exposure levels and associated guidance on improving IAQ. This system will go into multi-city trials involving a spread of demography and geography in Europe.

The importance of this work lies in the identification of the importance of monitoring IAQ and citizen's awareness in the whole process. This can lead to identifying the areas of further research such as indoor air pollution and health, developing different strategies to improve the air quality, raising indoor air pollution engagement at the citizen's level.

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