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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 becomes crucial to enhance IAQ and involving citizens in managing their indoor environments by raising awareness – a goal of a number of 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, are 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 data quality of such sensors so they could still be used reliably, often to provide indicative readings, and for analytics. In this work, we present data science-based techniques that we have 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 a number of 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 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 gives the opportunity to engage 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 this 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 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 the Section-II. The system architecture of Indoor Air Quality Monitoring, Kit design and experimental work is presented in the Section-III. Discussion and conclusion with the future works are presented in the 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 this week has estimated that 4.3% 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 AQ research field, is still a 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 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 including recently for IAQ monitoring [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 recent 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 show 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 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 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. Towards citizens' engagement in indoor air quality, Tiele et al. [27] have presented a low-cost sensor based indoor real-time monitoring system where researchers and interested citizens have been participated towards improving the indoor environment by experimenting with the 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 they determine the data [28]. Building such a system, Salman et al. [29] presented a real-time indoor air quality monitoring system with 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 which 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 low to allow the economics of scale. 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 use of structure data in the form of Knowledge Graphs from the outset, providing the potential for better search and visualization. In doing so, we present first usable Ontology – a knowledge structure required to build Knowledge Graphs – 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 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 indoor pollutants such as PM, CO_2, NOx, O_3, SO_2, radon, volatile and semi-volatile organic compounds (VOCs) and microorganism have recognised. Among these, some of the pollutants, PM, CO_2, NOx, O_3, SO_2 are also common to both indoor and outdoor environment [3, 7, 31]. Some of the pollutants such as CO_2, PM are heavily depending 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 our work we have considered following candidate sensors. This selection is based on other studies and experiments [23, 32-34].

- BME680: This sensor can measure temperature, humidity, barometric pressure and VOC gas.
- CJMCU-811: This sensor can be 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 can measure temperature, humidity and pressure, MICS6814 analog gas sensor is responsible to measure CO, NO_2 and Ammonia (NH3) and LTR-559 light and proximity sensor. Also, it has built-in ADS1015 analog-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 sensor selection that is reliable is a major challenge in building any AQ monitoring system. In order to finalise our IAQ monitoring kit, and to select 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, SDS011 sensor has a lower variance. In other words, SDS011 has shown higher linearity pattern in comparison to the other two sensors in the controlled lab environment as it can be observed in Figure 2 for $PM_{2.5}$ and Figure 3 for PM_{10}.

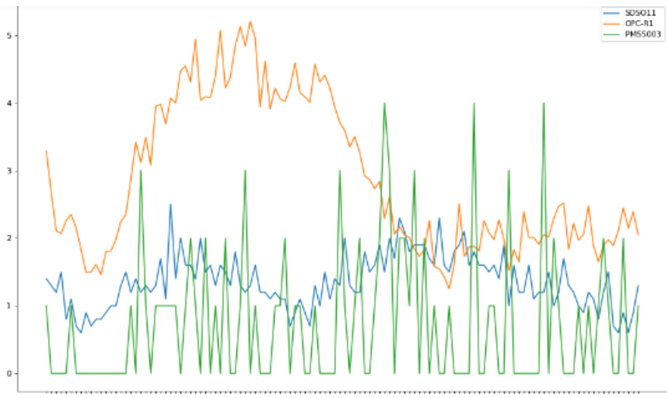

Figure 2: Comparison plot of PM sensors (SDS011: Blue, OPC-R1: Orange and PMS5003: Green) in a controlled lab environment (no human or any other mobility within the environment) for $PM_{2.5}$ over a period of 48 hours where the linearity of the plot is analysed as one of the sensor selection criteria.

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, we observed the density distribution of these three sensors readings as listed in Table I for $PM_{2.5}$ and Table II for PM_{10}

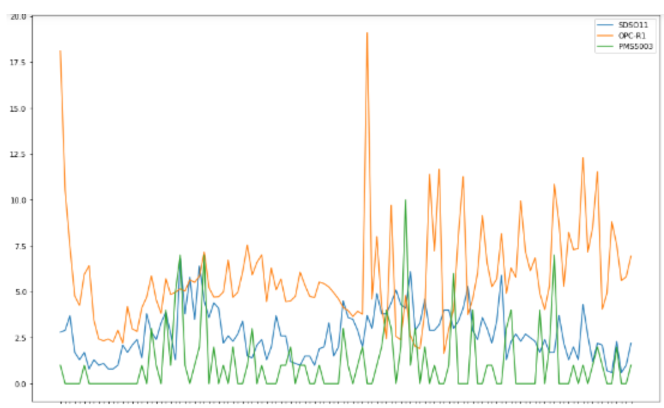

Figure 3: Comparison plot of PM sensors (SDS011: Blue, OPC-R1: Orange and PMS5003: Green) in a controlled lab environment (no human or any other mobility within the environment) for PM_{10} over a period of 48 hours where the linearity of the plot is analysed as one of the sensors selections criteria.

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. The SD value also reflected that SDS011 has better performance than the other two sensors in our experiment. We also inspected 90% distributed values to analyze the maximum value deviation from it. The observation shows that SDS011 sensor has the minimum deviation, for both $PM_{2.5}$ and PM_{10}, of the maximum value from the 90% distribution. We also analyse the drift 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 environment for 48 hours. The recorded data from one SDS011 sensor is compared to another SDS011 to analyze the drift between two data sets. Same approach is also applied to PMS5003. In general, data from the same environment recorded by two same sensors should have the minimum drift. In this case, we applied the Kolmogorov-Smirnov (KS) algorithm [36] to 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 on measuring in the same environment as compare to the PMS5003. From these analyses, SDS011 shows the best performance among the three PM sensors. These approaches guide to select the best viable sensor among different low-cost sensor options.

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 final IAQ kit is a combination of these multiple sensors and Raspberry Pi 3B+ to control the whole sensor kit. The Raspberry Pi have features like Bluetooth, 4 USB ports, Micro SD port for storage and access, wireless LAN, and 28 GPIO pins for external communication. All the sensors are connected with raspberry pi with the help of 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 to our web server.

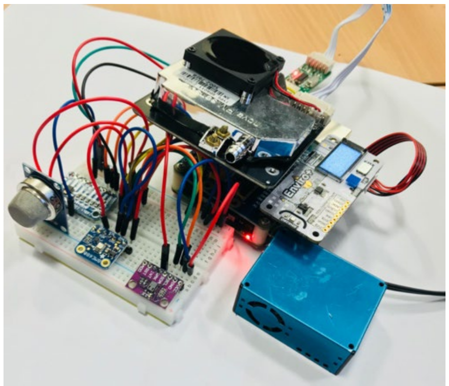

Figure 4: Final Sensor kit with IAQ sensors using Pi 3B+

Knowledge Graph

Data from the sensor kits are received and parsed using RESTful Application Program Interface (API) before storing into the data store. In our web service, the RESTful API, using 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]. We have developed an ontology for Air Pollution 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].

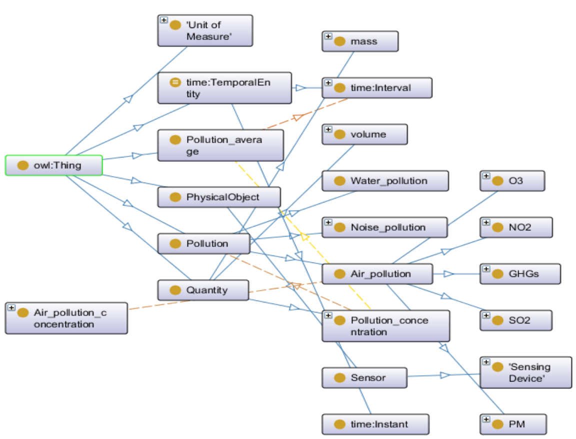

Figure 6: Graphical Representation of the Pollution Ontology – highlighting Indoor Air pollution branch structure.

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, 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 1day, 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).

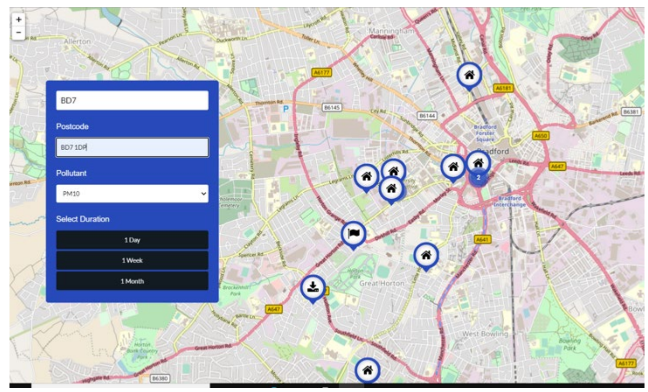

Figure 7.a: Visualising Sensor kits and data for indoor air pollution monitoring at one the city sites in the SCORE project. Citizens can search based on postcode and it will show IAQ devices in the searched geographic location.

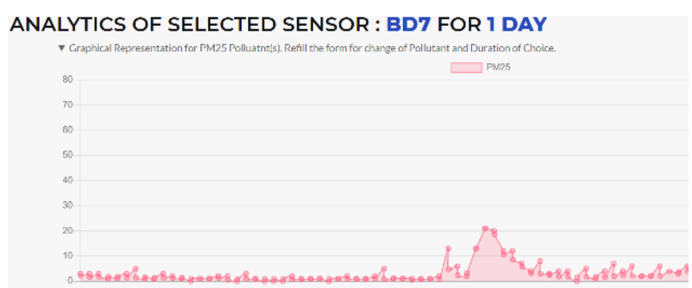

Figure 7.b: Visualising 1-Day time series plot of PM2.5 with varying reading with upper range 20 µg/m3, which below the WHO upper limit.

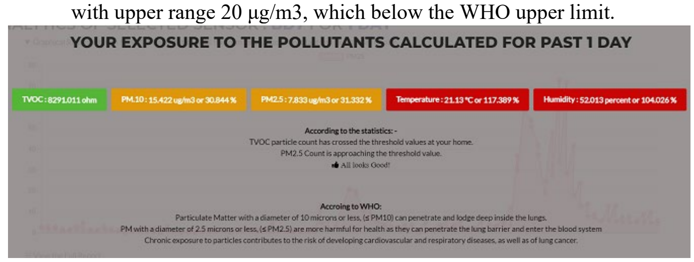

Figure 7.c: Visualisation system used by a Citizen shows them a summary of the pollutants in their homes and gives information on what the summary means and steps they can take to improve IAQ.

[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 a 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 really scale indoor air quality monitoring effort and bring much-needed impetus to this all-important area. In this work, an IAQ monitoring system is presented where the strategies on the selection of low-cost sensors are based on statistical methods and present use of Knowledge Graph with associated knowledge structure. Our system produces an interactive visualisation 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 citizen's level.

Acknowledgement

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