Environmental Data as Exposome and Opportunity of Combining with Cloud-Based Personal Health Records

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Abstract. The paper presents the efforts to clarify the usage of environmental data as exposome data that affect human health. According to the medical scientists, the exposome includes all exposure environmental factors, such as chemical and nonchemical agents, socio-behavioral and psychological factors as stress, diet, endogenous and exogenous factors from the whole lifespan. We consider the opportunities of combining a cloud-based Personal Health Record (PHR) with a particular patient's disease and exposome data gained from environmental databases connected with date, time and location of measurement as an influential factor of their good behavior. The main prerequisite for this concept has to be the existence of reliable sensors that have to provide the needed data for this purpose as well as PHR data, secured by patients. If the patient with some chronic disease will have reliable and available exposome data in a machine-readable format, these data can be used for assessment of the health risk for their specific disease connected with this specific environmental pollutant. This type of patient-centric possible data integration has to bring many benefits for patients and medical staff in the process of improvement of patient's care and self-care.

Keywords: Exposome, Personal Health Record (PHR), Environmental Data, E-health.

1 Introduction

Many efforts have been made to monitor the environmental parameters as factors that influence biological systems. According to the demands of EU regulative, the environmental parameters have to be measured and controlled as they affect human health and other biological systems, that are an obligation of government and municipalities authorities, especially now, in the era of IoT.

One of the biggest challenges in the next decade will be how the combination of genome and exposome data (as a whole of human exposures from birth to death) will contribute to reveal the risk factors for particular disease [5]. According to the medical scientists, the exposome includes exposure to environmental factors from chemical and non-chemical agents, socio-behavioral and psychological factors such as stress, diet, endogenous and exogenous factors from the whole lifespan [4]. Christopher P. Wild has defined three scopes of exposome: general (as social capital, education), internal (as metabolism, gene expression) and specific external (as chemical, noise, electromagnetic) [18]. Environmental data in combination with well-known data for health risk factors' limits of measured parameters can help to assess the risk for a specific disease.

Nowadays, it is a widely known fact that these massive data can hold many capabilities if they are processed and prepared appropriately. In the healthcare industry, these data can be reliable sources for environmental risk of some disease assessment, the risk for surveillance and population health management. Therefore, considering the amount of data generated from environmental parameters measurement, they can optimize the potential of healthcare environmental risk assessment for some specific disease in specific locations. These data are the key for optimizing the risk decreasing for some diseases taking into consideration the possibility for changing some habits, place of living and time for some activities, from patients and medical practitioners' perspective. It is a huge opportunity for data scientists to further improve environmental healthcare standards, given the overwhelming amount of environmental data being generated and stored. Their analysis can be very important in many management, policy-making and state levels.

In this IoT time, when the patients have an opportunity to have their own Personal Health Record (PHR) in a cloud environment [1] as the data owner, they can integrate their patient's healthcare and medical data with genome and exposome data as well as with Healthcare information systems' data from their Electronic Health Records (EHR), owned by hospitals and government. The ability to have a single dashboard for a patient's entire history is a big advantage for the patients, but when these data are combined with genome and exposome data, they can have a wider benefit. In other words, the patient's centric data integration can bring many advantages for the patient especially in the era of increased movement possibilities of patients and assessment of environmental risk factors for the patient's specific disease.

The paper describes how the real implementation of a cloud-based PHR system in the real pandemic environment with Cross4all project [1], can include health risk assessment from Exposome, with focus on environmental data. The current state of the Cross4all project is in the Pilot phase in two municipalities cross border, where the PHR data are already in the separate cloud servers databases on the two sides of the border with embedded preferences for GDPR regulations in two countries [8]. For more detail for the security model of web PHR you can referred the paper [8] and [2]. For Cross4all architectural model, more detail can be found in the paper [3]. In this paper, we propose the model of usage of Exposome data as external data sources for healthcare risk assessment for the particular patient, taking into consideration PHR data.

The proposed model takes into account one of the environmental parameter measurement for risk assessment. After the introduction, related works for this concept are considered. The next section describes some prerequisites for the concept implementation. After this section, some insights for time-series databases for environmental exposure data are considered and data visualized, providing some ideas about their integration with PHR data. The subsequent section discussed some usage of this kind of exposome data in specific disease concerns and propose some future usage. The concluding section considers the main idea of the paper and possible integration with PHR data and concludes the paper by drawing the possible ideas for future work.

2 Related works

The increased e-health possibilities and development of health information technologies nowadays creates a broad range of new opportunities in order to improve the healthcare services for citizens [1, 3]. With improved access to patients' data and giving the patients access to their health and treatment-related information, the patient is empowered with self-care management possibility as well as with the possibility to share their healthcare and medical data with selected medical persons [1, 3]. Also, an important segment of healthcare is healthcare costs, important for all healthcare stakeholders, especially for patients, physicians, and healthcare policymakers. They work to decreasing the healthcare costs whether it is possible to control costs while maintaining the quality of healthcare services at a higher, strategic level.

The important prerequisite for implementing the concept of e-health and increase the healthcare digital competency is the implementation of EHR, electronic medical records (EMR) and PHR. It is viewed as a critical step towards improvements in quality and efficiency in the healthcare system in many European countries [19]. EHR also can be seen as a repository of patient data in digital form, which stored and exchanged securely. We can mention also EPR (electronic patient records), as a sub-type of an EHR. ISO/DTR 20514:2005 standard [20] define EPR as a repository of patient data in digital form, stored, exchanged securely, and accessible by multiple authorized users. The EHR differs from EMR and PHR in the completeness of the information contains in the record and the custodian of the information designated. A PHR is described as a complete or partial health record under the custodian of a patient, the person(s) who holds the relevant health information about that person over their lifetime [1, 3].

The interoperability in healthcare can be explained as the possibility of exchanging healthcare data between two or more interconnected systems and can be understood in different ways. We choose the definition of Metzger et al. [21], where the interoperability of healthcare information system is defined as: 'the capability of heterogeneous systems to interchange data in a way that the data from one system can be recognized, interpreted, used and processed by other systems. This kind of interoperability can help in our intention to integrate our PHR data with exposome data [4] and provide environmental data that are available outdoor or indoor [23] that can be seen together with our PHR data. The cloud computing technology can offer such integration possibilities when PHR data are taken into account [1] considering patient's centric view, and enable intelligent agents to assess the data for patient's risk assessment and for the patient's health conditions and, according to medical staff to change some habit or event living place. Having PHR and EHR data in a cloud environment can give the advantage to share patient PHR with medical staff from healthcare institutions and provide medical staff to perform their tasks [22]. The PHR can be used, together with exposome data from environmental data sources for data for risk assessment for a particular disease, taken from PHR, according to the proposed model.

3 Prerequisites for using environmental data as the Exposome

The concept of exposome encompasses all non-genetic exposures of an individual from its conception to its lifetime. All of these influences complement the genome. The use of holistic and data-driven approaches that are similar to those defining genomic structure expects the concept of Exposome to result in advances in our understanding of the complex ecological component of disease etiology. The Exposome data are designed to include three overlapping and complementary domains:

1. A general external domain including macro-level factors such as climate, urban environment and societal factors;
2. An individual external domain including agents such as environmental pollutants, tobacco smoke, electromagnetic fields, diet and physical activity; and
3. A specific internal domain including gene expression, inflammation, and metabolism, often assessed through high-throughput molecular omics methodologies such as transcriptomic, proteomics and metabolomics [24].

Nowadays there are developed and are possible to apply novel tools and methods to obtain robust estimates of chemical and physical exposures in the outdoor environment (the outdoor exposome), focusing on key outdoor exposures (like outdoor air pollutants, noise, green space, UV radiation) [25]. Some of the measurement models that help the analysis are regression of air pollution in land use, urban noise maps, land use maps, raster maps of land surface temperature, building density, population density, connectivity, walkability and public bus transport map information for the built environment, and meteorological data, etc. Data from existing regulatory monitors were used to support the extrapolation of ambient air exposure models. Such data are collected and public available by the Ministry of Environment and Physical Planning [7].

The effect of the exposome on specific highly prevalent health outcomes are pre- and post-natal growth and obesity, asthma and respiratory function, and neurodevelopment. Besides inter- and intra – individual variability in specific subpopulations or strata that are of importance to Exposome studies should be characterized, including those in critical periods of life (including in utero, early life, and old age) where susceptibility to adverse consequences of exposure may be increased. Such subpopulations exist in the European Union FP7-funded HELIX [7] (Human Early-Life Exposome) project. This project is focused on studying the early life exposome by combining six mother-child cohorts in Europe: UK, France, Spain, Lithuania, Norway, and Greece, where a total of 1200 mother-child pairs were selected for exposome characterization using a multitude of analytical approaches, including both internal and external measures, and it portrays an early coordinated effort to advance exposome research.

Humans are exposed to thousands of species with great intra-species diversity, which demonstrates that the human Exposome is highly dynamic and influenced by spatial/lifestyle and seasonal variables [26]. The concept of an Exposome network based on the extensive interactions among the organisms and associations between organisms and chemicals can be partitioned into a stable human-centric cloud and a more dynamic environment-centric cloud. That way the data will be valuable for many scientific fields, including public health, microbiome, environmental science, evolution, and ecology. Human-centric cloud will store PHR and its architecture is stable and highly secured [8]. The environment-centric data is stored in a time-series database cloud because of its diversity values in a time frame. Another storage that should be connected in this architecture is knowledge of diseases related to ecological influences – chronic composition of the patient group and monitoring of parameters that have influences on intensification of the disease [26].

An obstacle for dealing with environmental factors and the parameters measured is the lack of sufficient knowledge of the relation with diseases. 24% of the world's deaths are linked to the environment (2016) [9]. That's roughly 13.7 million deaths a year. 8.5 million of those cases are due to non-communicable diseases like ischemic heart diseases (2.4 million), chronic respiratory diseases (1.9 million), cancers (1.8 million), unintentional injuries (1.5 million), respiratory infections (1.5 million), stroke (1.5 million), diarrheal diseases (829 000), diabetes (391 000), malaria (355 000), neonatal conditions (244,000) etc. [9].

Air pollution can increase the risk of respiratory diseases, increasing the susceptibility to viral and bacterial infections. Some studies suggest that small particles in the air facilitate the spread of viruses, as well as the new Covid-19, in addition to direct person-to-person infection. However, the effects of exposure to particles and other pollutants are poorly understood. The possible reasons for the patient's health depend a lot on the environment in which he is, resides and lives. The latest finding is that among several environmental, health and socio-economic factors, air pollution and particulate matter (PM2.5), as its main component, result as the most important predictors of patient health. It has also been found that emissions from industry, farm and road traffic – in importance – may be responsible for more than 70% of deaths nationwide [10]. Given the greatest contribution of air pollution (much more important than other health and socio-economic factors), it is predicted that, by increasing air pollution by 5-10%, similar future pathogens could increase epidemic growth by 21 -32%. According to the findings, the level of particulate pollutants (PM2.5) is the most important factor in predicting the effects of viruses – such as SARS-CoV-2, which will worsen even with a slight reduction in air quality [10].

The PHR data existence is one of the prerequisites for creating such a model for usage of environmental data as Exposome together with PHR data [1]. They should have a secure architecture [3] with a defined security model [2] [8]. The environmental data as Exposome [4] also should be available for the wider population, only with basic security setting, without high-security prerequisites. Some data for environmental exposome boundaries or allowed limits of parameters also have to be known in order to provide information for higher values for the environmental measured parameters. In addition, the environmental factors (parameters) can be connected with some diseases [5] and creating some knowledge about this, that can be a big obstacle for model validation.

4 Time series databases used in collecting environmental metrics per location

Collecting and analyzing big data of air pollution with labeled thresholds can give efficient metrics for the environmental factors and exposure of personal health. For example, in Fig. 1 we can see real-time metrics for a specific location and the dynamics of data collected in the time frame. Limits and target values for SO2, NO2, CO, PM10, PM2.5, O3, benzene, PAHs and heavy metals are defined in order to protect human health. The alert threshold indicates a level of concentration above which there is a risk of short-term exposure to human health as a whole and if immediate steps need to be taken to improve air quality. The atmosphere inevitably plays a massive role in our health such as the impact on DNA damage, metabolism, skin integrity, and lung health. Also, poor indoor air quality can cause various infections, lung cancer, and chronic lung diseases such as asthma. The following table defines the alert thresholds for SO2 and NO2 concentrations, as well as the information and alert thresholds for ozone and PM10, marked on the official website of the Ministry of Environment and Physical Planning [11].

To improve air quality and minimize pollution-related deaths, we must identify, measure, and analyze our atmosome data to study how the air we breathe affects our health. Exposome research is expanding rapidly and public environmental data is becoming more detailed and accessible. The sensors collect data and send the readings to the cloud. The cloud system provides a REST API for retrieving and posting data. It also comes with an API to query based on specific locations. Users and researchers can easily collect and parse this data to generate graphs and study patterns over time. Fig. 2 shows a sample of collected data from different sensors on different locations labeled/tagged with code "shifra" (eq. 7948 – area "Jeni Maale",7974 – area "Oblasta", 7975 – area "Shirok Sokak" etc.).

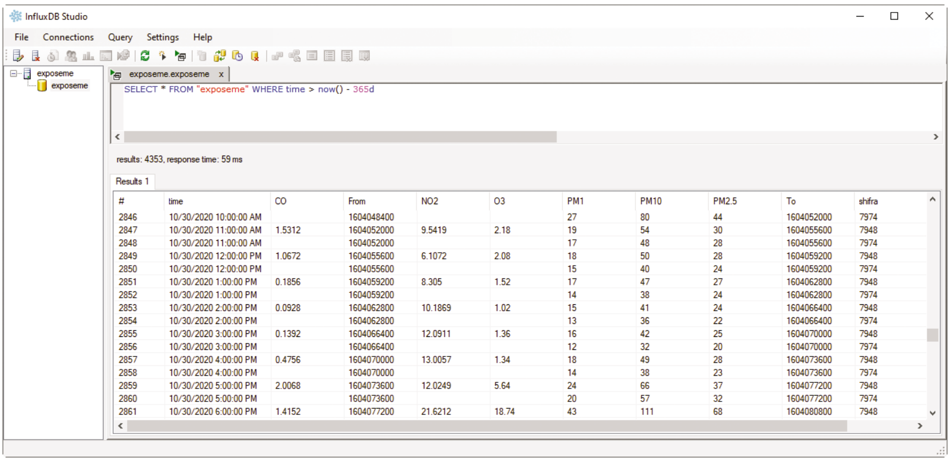
Many tools provide an interactive graphical user interface to adjust the parameters of analytical methods (e.g., via sliders or checkboxes). Visualization views can usually be adjusted via common view navigation (zoom, pan, and rotation), dynamic queries, time frames etc. Such a tool is Grafana where the visualization of the data over the time frame is remarkable through different panels and efficient query languages like InfluxQL, Flux, PromQL or PostgreSQL (Fig. 2).

To improve air quality and minimize pollution-related deaths, we must identify, measure, and analyze our atmospheric exposome (atmosome) to study how the air we breathe affects our health. Exposome research is expanding rapidly and public environmental data is becoming more detailed and accessible. In North Macedonia, the problem with air pollution is alarming because as we can see from the data collected in Fig. 2 and Fig. 3 there are quite a high number of measurements that are above the critical threshold and that period represent the red zone especially for the people with chronic diseases. That is one of the main reasons for a higher rate of deaths (around 30%) compared with other countries with higher awareness for the exposome relations to public health.

Table 1. Pollutant thresholds table published on the official website of the Ministry of Environment and Physical Planning in RN Macedonia [11].

Pollutant	Limit or target value			Long-term goal	Thresholds for information and alert	
	Average period	Value	Number of allowed exceedances	Value	Period	Threshold value
SO_2	Hour	350 $\mu g/m^3$	24		3 Hours	500 $\mu g/m^3$**
	Day	125 $\mu g/m^3$	3			
NO_2	Hour	200 $\mu g/m^3$	18		3 Hours	400 $\mu g/m^3$**
	Year	40 $\mu g/m^3$	0			
Benzene	Year	5 $\mu g/m^3$	0			
CO	Maximum daily 8-Hour average	10 mg/m^3	0			
PM_{10}	Day	50 $\mu g/m^3$	35		2 Days	100 µg/m3 and a stable weather forecast *
	Year	40 $\mu g/m^3$	0		2 Days	200 µg/m3 and a stable weather forecast**
$PM_{2.5}$	Year	25 $\mu g/m^3$	0			
Pb	Year	0.5 $\mu g/m^3$	0			
As	Year	6 ng/m^3	0			
Cd	Year	5 ng/m^3	0			
Ni	Year	20 ng/m^3	0			
B(a)P	Year	1 ng/m^3	0			
O_3	Maximum daily 8-Hour average over 3 years	120 $\mu g/m^3$	25	120 $\mu g/m^3$	1 Hour	180 $\mu g/m^3$*
					3 Hours	240 $\mu g/m^3$**
** alert threshold						
* information threshold						

Our system is very effective in detecting alert events, because of its capabilities to collect and send data to the cloud in real-time. Particulate matter refers to mixtures of microscopic solid and liquid particles suspended in the air. Two types of particulate matter are most relevant to air pollution: PM10 and PM2.5. PM10 refers to particles that are between 2.5 and 10 microns; some examples of these include dust, pollen, and particles of mold. PM2.5 consists of fine particles that are 2.5 microns in diameter or less; fuel combustion, cigarette smoke, aerosols, and more can form them. Particulate matter is a health risk because it is small enough to be inhaled and deposits itself in the airways of the human body. The smaller particles can even lodge themselves deep in the lungs or enter the bloodstream. Even short-term exposure to PM10 has been associated with worsening respiratory diseases and can lead to emergency room visits. Long-term exposure (months to years) has been linked to premature death, especially in people with chronic conditions, and leads to reduced lung function in children [12]. WHO recommends a maximum exposure of 20 μg/m3 for PM10 and a maximum exposure of 10 μg/m3 for PM2.5 [13]. Besides these, which are outdoor collected metrics, measuring particulate matter in indoor air can lead to user implementable corrective actions. That can be achieved by collecting data from different wearable devices and smartphone applications and presents many opportunities for personal health estimation and navigation. Such sample system is AMS (Atmosome Measurement System) [14].



#	time	CO	From	NO2	O3	PM1	PM10	PM2.5	To	shifra
2846	10/30/2020 10:00:00 AM		1604048400			27	80	44	1604052000	7974
2847	10/30/2020 11:00:00 AM	1.5312	1604052000	9.5419	2.18	19	54	30	1604055600	7948
2848	10/30/2020 11:00:00 AM		1604052000			17	48	28	1604055600	7974
2849	10/30/2020 12:00:00 PM	1.0672	1604055600	6.1072	2.08	18	50	28	1604059200	7948
2850	10/30/2020 12:00:00 PM		1604055600			15	40	24	1604059200	7974
2851	10/30/2020 1:00:00 PM	0.1856	1604059200	8.305	1.52	17	47	27	1604062800	7948
2852	10/30/2020 1:00:00 PM		1604059200			14	38	24	1604062800	7974
2853	10/30/2020 2:00:00 PM	0.0928	1604062800	10.1869	1.02	15	41	24	1604066400	7948
2854	10/30/2020 2:00:00 PM		1604062800			13	36	22	1604066400	7974
2855	10/30/2020 3:00:00 PM	0.1392	1604066400	12.0911	1.36	16	42	25	1604070000	7948
2856	10/30/2020 3:00:00 PM		1604066400			12	32	20	1604070000	7974
2857	10/30/2020 4:00:00 PM	0.4756	1604070000	13.0057	1.34	18	49	28	1604073600	7948
2858	10/30/2020 4:00:00 PM		1604070000			14	38	23	1604073600	7974
2859	10/30/2020 5:00:00 PM	2.0068	1604073600	12.0249	5.64	24	66	37	1604077200	7948
2860	10/30/2020 5:00:00 PM		1604073600			20	57	32	1604077200	7974
2861	10/30/2020 6:00:00 PM	1.4152	1604077200	21.6212	18.74	43	111	68	1604080800	7948

Fig. 1. Time series database of collected pollutant values.

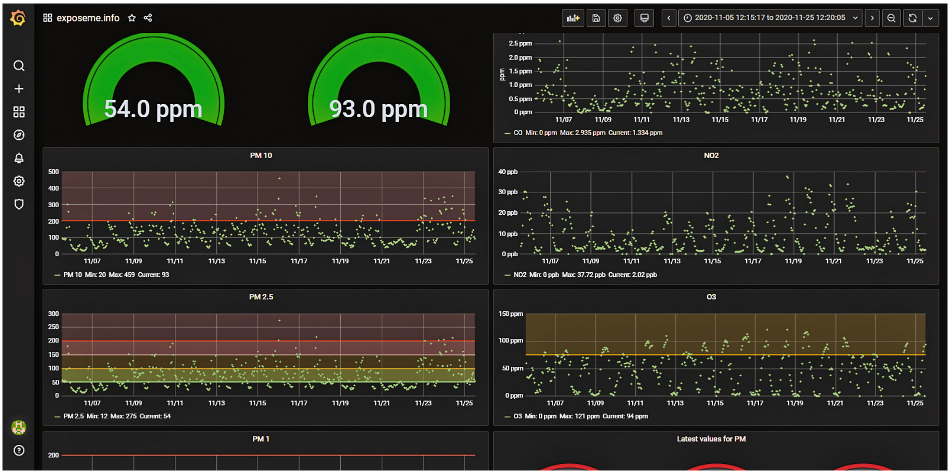


Fig. 2a. Pollutant metrics visualized in Grafana Dashboard.

Fig. 2b. Pollutant metrics visualized in Graph panels with thresholds for the time period.

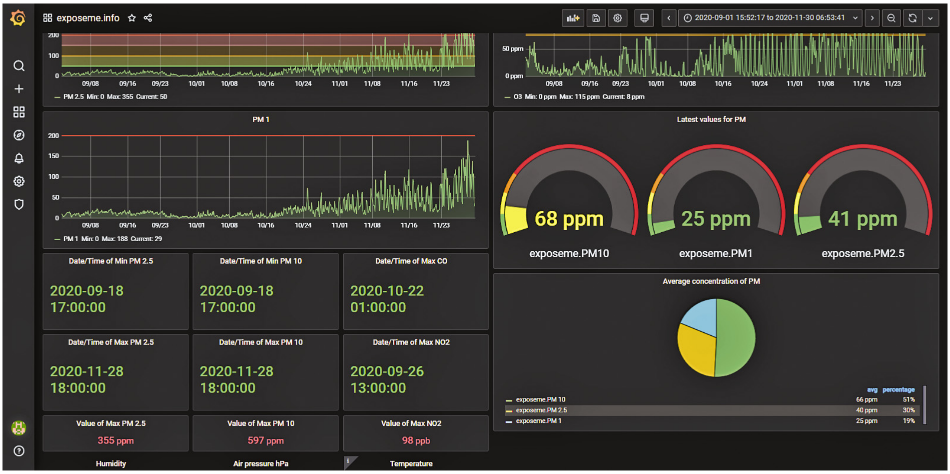


Fig. 3. Visualization of pollutant metrics in Grafana Dashboard. Different panels are created for emphasizing the alert date time periods where max values above critical thresholds are exceeded.

If a physician or user could access this kind of data regularly, they would gain insights on how their behavior and surroundings affect human bodies and take tangible steps towards staying healthy in traffic on vacation or other similar situations.

When it comes to integrating data, Chris Gennings cautioned that big data are not always better. She emphasized that big data are usually more complex and should be used to conduct hypothesis-driven and confirmatory research, not just used in an exploratory manner. Another concern with big data is that they can make any finding look significant in the traditional statistical sense, but they may have an effect size that might not be critically meaningful. One strategy is to integrate data from disparate study types, such as those linking environmental exposures and health outcomes on the assumption that exposure in a certain locality might be relevant to health outcomes in those localities. Gennings noted that a variation of this strategy involves linking human data with experimental study results, as in the case of the European Union's EDC-MixRisk project, which links laboratory studies on endocrine-disrupting chemicals with data from two birth cohorts to suggest what realistic relevant exposures might be and generate a risk assessment [15]. Another strategy is to integrate data across epidemiology studies. One goal of this strategy is to increase generalizability by combining, for example, multiple exposure studies from many different locations around the country.

Geocoding using mobile sensors, zip codes, and questionnaires will be important for using EHR data in environmental health studies given that most environmental exposure data are not captured in the EHR today [15] [16]. However, there are databases with geo-located environmental data that could be integrated with her or PHR data. The one caution is that a person's address is a Health Insurance Portability and Accountability Act – HIPAA identifier, making it important to have the proper institutional research board protections in place and to have patient consent to use geolocation data.

Pediatric Research using Integrated Sensor Monitoring Systems (PRISMS) project from the National Institute of Biomedical Imaging and Bioengineering launched in 2015, aims to develop sensor-based, integrated health monitoring systems for measuring environmental, physiological, and behavioral factors in pediatric epidemiological studies of asthma and eventually other chronic diseases. Asthma affects 1 in 12 people. The idea is that patients and various sensors will interact with PRISMS through smartphones or smartwatches that will securely upload data to the project's informatics platform and data coordinating center. This individual-level data will be linked with external environmental data from sources such as Environmental Agency's monitoring networks or pollen counts and with EHR data. After synchronizing and integrating these data sources, PRISMS investigators will conduct predictive modeling that can be fed back to the patient or parent to both engage the patients and encourage patient compliance with an asthma management plan. Health care providers may also receive information from the system. Children participating in PRISMS will receive smartwatches that can collect real-time data from built-in GPS, accelerometers, and gyroscopes, which will provide a measure of the child's activity and microenvironment. Children will also carry portable Bluetooth-enabled spirometers, so-called smart inhalers that provide a geolocation and time stamp with every use and sensors that can sample the environment and provide a personal measurement of exposure to air pollution. The project team is working on methods to process the torrent of data these sensors will generate, align the different sensor data streams, integrate them with external data sources, and use advanced analytics, including machine learning, to cluster patients and make predictions from individual baseline measurements, explained Sandrah Eckel from the University of Southern California [15].

Experimental exposure to PM results in oxidative stress, airway hyper-responsiveness, and airway remodeling, either alone or in combination with allergic sensitization. Short-term exposure to ambient PM2·5 and PM of diameter 2·5–10 μm in prospective cohorts of asthmatic children and adults has been associated with asthma symptoms, especially in children with allergic sensitization. Long-term exposure to PM is associated with poorly controlled asthma and decrements in lung function in children and adults. Several studies in children and adults have shown associations between short-term and long-term exposure to PM2·5 or PM10 and increased healthcare use. These associations are generally partially attenuated but persistent after adjustment for co-pollutants [17].

Some evidence suggests PM is a cause of incident asthma. Independent associations between exposure to PM10 in utero and during infancy with asthma diagnosed by a doctor were identified in a nested case-control study within a large birth cohort. Although several studies have identified associations between asthma prevalence and exposure to outdoor PM, this finding has not always been consistent. Furthermore, PM is frequently strongly correlated with ozone, nitrogen oxides, and Sulphur oxides, serving to confound these associations. In summary, substantial evidence supports the idea that ambient levels of PM exacerbate existing asthma, particularly by contributing to oxidative stress and allergic inflammation, and some evidence exists in support of PM as a cause of new cases of asthma (Fig. 4) [17].

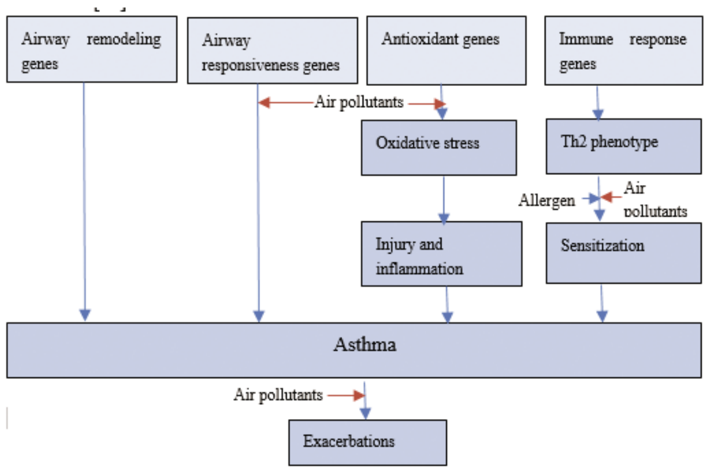


Fig. 4. Mechanistic framework for air pollution effects in asthma [15].

5 Results and discussion

With the help of artificial intelligence, the importance of air pollution for the mortality rate of patients is studied cross the latest several years. The ultimate goal is to link exposure and health outcome datasets to identify, propose, test, implement, and evaluate potential interventions. Today, the sources and types of data available for integration and analysis are almost limitless, so it is important to first decide on the key questions of interest and then identify the data needed to answer those questions to the desired level of accuracy and precision. Next comes a reality check in terms of the data available, the methods to access and analyze those data, and the questions that can be answered with those data and methods. Here, we are not emphasizing the data integration in terms of finding the perfect data to answer a question but instead, we present data integration as a process for bringing together available datasets in creative and informative ways to help refine research questions and inform the next cycle of data acquisition and analysis. One of the main thrusts of data science, and particularly artificial intelligence, is not just solving problems faster by using existing methods designed for “small” datasets, but rethinking the analytical problem from the lens of being able to bring in more data, integrate them in new ways, and calibrate results with what is already known about a particular problem.

The examples created from environmental data for this paper highlighted just a couple of possible usage of the environmental Exposome and their integration with PHR data, as is shown in the Fig. 5. This research has to explain the proposed model by using these environmental exposome data. The model should be validated through examples of risk assessment for specific patient’s PHR as an influencing factor of these pollutants to some specific patient’s disease in order to have a clear understanding of this influence of the patients’ health. For this purpose, methods for machine learning or decision-making by evaluating the associated costs and health benefits of mitigation actions against climate change can be used to create some algorithm for risk assessment that contains the mathematical estimation and modeling of several processes, including population estimates, population exposure to pollutants, and adverse health impacts assessment through specific concentration-response functions [27].

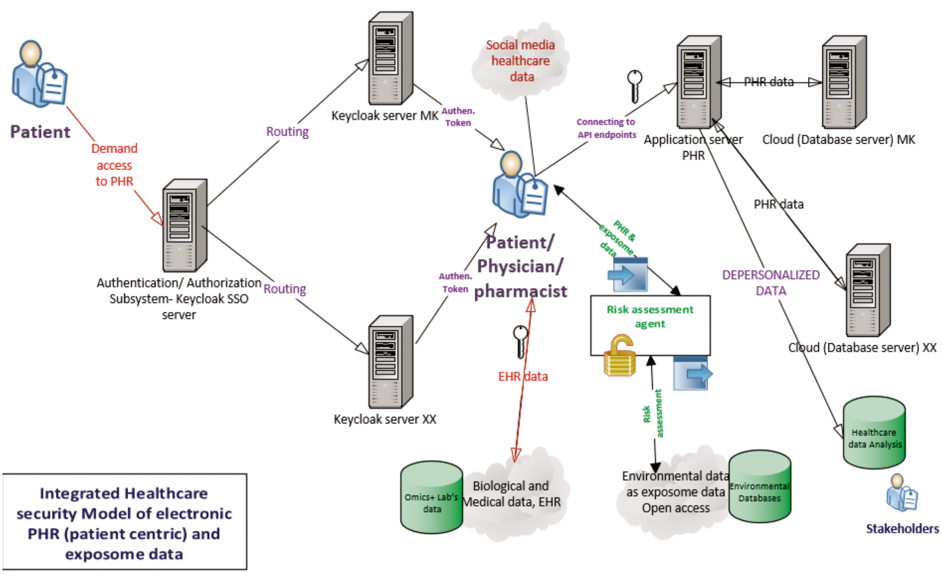


Fig. 5. Integrated Healthcare Model of Electronic PHR and Exposome data.

6 Conclusion

A portion of complex disease risk is likely due to the interaction of inherited genetic and non-inherited environmental factors. A substantial body of research on the effects of air pollution on asthma has been published in the past years, adding to the body of knowledge that has accumulated over several decades. Presently, short-term exposures to ozone, nitrogen dioxide, Sulphur dioxide, PM2·5 is thought to increase the risk of exacerbations of asthma symptoms and a lot of other diseases. Increasing amounts of evidence also suggest that long-term exposures to air pollution contribute to a high percentage of deaths between adults even children. Much more about the mechanisms that are involved with exacerbations induced by pollution needs to be understood, but oxidative stress and immune dysregulation are probably both involved.

We examined a part of data collected in a time series database in our close area and presented and visualized it by using a tool whereas very easy we can identify the limits and thresholds exceeded. Such overriding is causing alarm, especially for people with chronic diseases. The alarm can be a caution associated with the PHR and can inform the person and his medical practitioners for the situation, which can help in diagnose and prevention. Considering the implementation of similar solutions for the hardware used for gathering data and acknowledge the necessity of having that data available for calculations, machine learning methods can be used to provide a prediction, precision, and great presentation of the patient health status.

7 Acknowledgement

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References

1. Snezana S. et al. (2020) Cloud Based Personal Health Records Data Exchange in the Age of IoT: The Cross4all Project. In: Dimitrova V., Dimitrovski I. (eds) ICT Innovations 2020. Machine Learning and Applications. ICT Innovations 2020. Communications in Computer and Information Science, vol 1316. Springer, Cham. https://doi.org/10.1007/978-3-030-62098-1_3
2. Savoska S., Jolevski I., Ristevski B., Blazeska-Tabakovska N., Bocevska A., Jakimovski B., Chorbev I., Kilintzis V., Design of Cross Border Healthcare Integrated System and its Privacy and Security Issues, In Proceedings of Computer and Communications Engineering, Workshop on Information Security, 9th Balkan Conference in Informatics, Volume 13, 2/2019, Pp.58-64

3. Savoska S., Jolevski I., Architectural Model of e-health PHR to Support the Integrated Cross-border Services, In proceedings of ISGT conference 2018, pp. 42-49, Sofia, 2018.
4. Savoska S., Ristevski B., Blazheska-Tabakovska N., Jolevski I. Towards Integration Exposome Data and Personal Health Records in the Age of IoT. In: 11th ICT Innovations Conference 2019, 17-19 October, Ohrid, Republic of Macedonia.pp.237-246, 2019.
5. Barouki R., Audouze K., Coumoul X., Demenais F., Gauguier D., Integration of the human exposome with the human genome to advance medicine. Biochimie, Elsevier,2018, 152, pp.155-158. 10.1016/j.biochi.2018.06.023. hal-02196327
6. Wild C.P., Complementing the genome with an "exposome": the outstanding challenge of environmental exposure measurement in molecular epidemiology, Cancer Epidemiol Biomarkers Prev. 14 (2005) 1847-1850.
7. Vrijheid M, Slama R, Robinson O, Chatzi L, Coen M, van den Hazel P, Thomsen C, Wright J, Athersuch TJ, Avellana N, et al. The human early-life exposome (HELIX): project rationale and design. Environ Health Perspect. 2014;122:535–44.
8. Savoska S., Jolevski I.,Ristevski B., Blazeska-Tabakovska N., Bocevska A., Vassilis K., Chorbev I., Jakimovski B., Chapter The Model Of Healthcare Integrated System And Solving Security And Privacy Matters In Personal Health Records
9. WHO World Health Organization Brochures: Public Health England WHO Infographic_Final-English_07March https://www.who.int/quantifying_ehimpacts/publications/PHE-prevention-diseases-infographic-EN_up2016_red.pdf?ua=1, Published June 2016
10. Cazzolla Gatti R., Velichevskaya A., Tateo A., Amoroso N., Monacoe A., Machine learning reveals that prolonged exposure to air pollution is associated with SARS-CoV-2 mortality and infectivity in Italy; https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7442434 Published online 2020 Aug
11. Official site of Ministry of Environment and Physical Planning in the Republic of Northern Macedonia: https://air.moepp.gov.mk/
12. California Air Resources Board. Inhalable Particulate Matter and Health (PM2.5 and PM10) — California Air Resources Board, 2020.
13. WHO World Health Organization. WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: Global update 2005. Technical report, 2005
14. Bhimaraju H., Nag N., Pandey V., Jain R., Atmosome: The Personal Atmospheric Exposome, Published July 6, 2020
15. Informing Environmental Health Decisions Through Data Integration Proceedings of a Workshop—in Brief (2018), 1-11
16. Ritchie, M. D., J. C. Denny, D. C. Crawford, A. H. Ramirez, J. B. Weiner, J. M. Pulley, M. A. Basford, K. Brown-Gentry, J. R. Balser, D. R. Masys, J. L. Haines, and D. M. Roden. 2010. Robust replication of genotype-phenotype associations across multiple diseases in an electronic medical record. American Journal of Human Genetics 86(4):560–572. doi: 10.1016/j.ajhg.2010.03.003.
17. McCarty C. A., R. Berg, C. M. Rottscheit, C. J. Waudby, T. Kitchner, M. Brilliant, and M. D. Ritchie. 2014. Validation of PhenX measures in the personalized medicine research project for use in gene/environment studies. BMC Medical Genomics 7:3. doi: 10.1186/1755-8794-7-3.
18. Guarnieri M., and J. R. Balmes, Outdoor air pollution and asthma. Lancet. 2014 May 3; 383(9928): 1581–1592.
19. Bashshur, R.L., Shannon G., Krupinski E.A. et al.: Sustaining and realizing the promise of telemedicine. Telemedicine journal and e-health, Vol. 19. No. 5, 339-345. (May 2013)
20. ISO/DTR 20514:2005 (2005) Health Informatics-Electronic Health Record- Definition, Scope, and Context. [Online] Available at: http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=39525

21. Metzger M.H., Durand T., Lallich S., et al.: The use of regional platforms for managing electronic health records for the production of regional public health indicators in France. BMC Medical Informatics and Decision Making Vol. 12, 28. (2012)
22. Fernández-Cardeñosa G., De la Torre-Díez I., Rodrigues J.J.P.C.: Analysis of the Cloud Computing Paradigm on Mobile Health Records Systems. In: Proceedings of the Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, Palermo, Italy, July 2012, pp. 927-932. IEEE Computer SocietyWashington, DC, USA. (2012)
23. Bhimaraju H. et al., Atmosome: The Personal Atmospheric Exposome, CC-BY-NC-ND 4.0 International license, medRxiv a license to display the preprint in perpetuity. July 6, 2020. .https://doi.org/10.1101/2020.07.02.20145433doi:
24. Santos S., Maitre L., Warembourg C., Agier L., Richiardi L., Basagaña X., Vrijheid M., Applying the exposome concept in birth cohort research: a review of statistical approaches, European Journal of Epidemiology volume 35, pages193–204(2020)
25. Project Final Report HELEX – "The Human Early-Life Exposome novel tools for integrating early-life environmental exposures and child health across Europe", ENV-FP7-2012-308333, https://cordis.europa.eu/project/id/308333/reporting, 4/13/21
26. Jiang C., Wang X., Li X., Inlora J., Wang T., Liu Q., Snyder M., Dynamic Human Environmental Exposome Revealed by Longitudinal Personal Monitoring, Volume 175, Issue 1, 20 September 2018, Pages 277-291.e31
27. Tavoos H. B., Guo J., Hooman F., Air Pollution Health Risk Assessment (AP-HRA), Principles and Applications, Int. J. Environ. Res. Public Health 2021, 18(4), 1935; https://doi.org/10.3390/ijerph18041935, 17 February 2021