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Summary

Globally, Artificial Intelligence (AI) is gaining momentum. Developments in technologies have empowered citizens to make extensive contributions. Citizen Science (CS) has attributed to both social and technological benefits. In the fields of citizen science and urban development, implementation of new technologies offers some enormous opportunities. CS can channelize rampant technologies and systems that are commonly grown such as sensor technology for air quality (AQ) monitoring. Machine Learning, deep learning and big data analysis are generating deep insights in addressing environmental and urban issues. With advances in technology, significant questions are emphasized concerning human ethics. And, with the involvement of citizens, especially, technologies impact and role in society are broadly questioned.

In this study, the case study Hollandse Luchten Pilot is analysed in North Holland. The core objective of the research is to explore the opportunities and risks of AI to enhance the quality of CS AQ data, to explain the factors influencing the integration of AI tools and CS initiatives for AQ assessment in the case of the Hollandse Luchten pilot project and to draw conclusions that can enhance the implementation of the project, especially the AQ data collected by citizens.

Case Study was selected as the strategy, regarding the research methodology. Eleven semi-structured interviews were conducted with experts from the field of AI, experts from the organizations involved with the Hollandse Luchten Project and the Community Leaders. Additionally, secondary data was analysed to support the primary data collection.

The research revealed that AI methods can be integrated with the different aspects in the process of CS AQ monitoring, namely, data analysis (especially calibrations), optimization of location and increasing resolutions (using satellite imageries). The socio-technical factors play a vital role in mediating the relationship between the AI and the quality of CS AQ data. AI offers a remarkable opportunity in overcoming data gaps, which indirectly affects citizens perception and participation cycle. These factors are crucial in fulfilling society's goals of enhancing their living environment.

To conclude, appropriate management of data, especially, regarding data reliability and accuracy, that can fulfil their roles of empowering communities, must be critically considered and analysed. To maximise the impact of CS data, CS projects should adopt AI methods and tools that enable the use of large volumes of data from known or unknown sources, across platforms and stakeholders to increase data quality and accuracy. Consequently, CS will be able to intensify and reach its remarkable potential for progressing environmental research for a project like Hollandse Luchten.

Keywords

Artificial Intelligence, Machine Learning Citizen Science, Air Quality, Socio-technical factors,

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Abbreviations

AI	Artificial intelligence
ML	Machine Learning
SDGs	Sustainable Development Goals
GHG	Greenhouse gasses
IPCC	Intergovernmental Panel on Climate Change
CS	Citizen Science
RIVM	National Institute for Public Health and the Environment, Ministry of Health, Welfare and Sport
AQ	Air Quality
ESA	European Space Agency
CSEOL	Citizen Science Earth Observation Lab
EEA	European Environment Agency
EU	European Union
WHO	World Health Organization
PM	Particulate Matter
EPA	U.S. Environmental Protection Agency
CO	Carbon Monoxide
NO_2	Nitrogen Oxide
SO_2	Sulphur Dioxide
O_3	Ozone
Pb	Lead
LUR	Land-Use Regression
EC	European Commission

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Chapter 1: Introduction

This study focuses on exploring the possibilities of integrating artificial intelligence (AI) methods, a layer of technology that can be used in the field of Citizen Science (CS), specifically in the context of Air Quality (AQ) data monitoring. For this study, the opportunities and risks associated with AI are analysed in-depth and the factors of citizen participation affecting the quality of data are evaluated. For this purpose, this section commences by briefly explaining, the use of AI in addressing numerous urban issues, the role of CS, and the introduction of the case- CS AQ pilot project, Hollandse Luchten in North Holland, thereby conceptualizing the problem statement.

1.1 Background

AI is a vital enabler for addressing *climate change* and various other socio-economic, and environmental issues existing in the urban areas. The emergence of AI is shaping an increasing range of sectors affecting global productivity (Acemoglu, 2018), equality and inclusion (Bolukbasi 2016), and environmental outcomes (Norouzzadeh, 2018). The dawn of the fourth industrial revolution for Earth Initiative has perceived an upsurge of AI in various sectors of addressing crucial challenges in spatial planning, biodiversity and conservation, water systems, air, and ecosystems. AI is expected to have a cordial impact, not only by pervading all the traditional industries but also by playing a vital role in daily lives. The capabilities of AI are intrinsic, which extend its branches to a vast variety of potentials required to address *climate change* challenges efficiently. According to World Economic Forum Report (2018), in the forthcoming decades, the average home computer will have as much power as the current supercomputer through the advanced AI algorithms and simultaneously, Machine Learning (ML), will also in a broad perspective, unlock faster and cheaper earth systems and climate models. The report also suggests the replacement of many labour-intensive and time-consuming tasks done by scientists, for example, from examining through data archives to converting files. This will be done by simple AI algorithms, acting as an 'AI research assistant'. The outcome of such technology would also include access to AI tools that would progress in Earth science, whose application could become regular. This could further boost scientific productivity with a subsequent quickening in discoveries. These discoveries could act as a breakthrough in the understanding of weather risk, challenging areas like climate feedback loops and tipping points, and future regional and local climate impacts.

According to Vinuesa, (2020), an array of technologies is being established at a fast rate, affecting individual lives and its effects on the environment. This requires appropriate legislation and adequate policies from the government to safeguard the long-term viability of these new technologies. The initial step is to direct the potential of AI towards the assistance of the individuals, environment as well as the achievement towards the Sustainable Development Goals (SDGs) (Vinuesa, 2020). However, there is a limited understanding of the potential impact of AI on institutions. For all the immense potentials of AI for a future sustainable planet, AI also stances a series of risks and limitations with varying impacts on individuals, society, and the earth. Recent studies have indicated that one of the major limitations of AI, according to Green et al., (2020) is social exclusion because of the unacceptability of technology, and the challenge of analysing the acquired data collected. This study aims to explore the possibilities of AI only in a specific field of community participation, also known as Citizen Science (CS), which is discussed further in the section.

The challenge of the impassiveness and detachment of the community from the substantial scientific research processes could be addressed by community participation and citizen engagement tools such as '*Citizen Science'*. National Institute for Public Health and the Environment, *Ministry of Health, Welfare and Sport, (RIVM) the Netherlands*, initiate various environmental monitoring networks where numerous organizations and citizens collaborate and conclude CS as the 'New way of looking at the world'. Although CS has been a popular citizen-engagement tool in various researches, the contribution of CS in space-data research programs is not well known, especially when the various AI or Machine Learning (ML) methods are involved in the data analysis processes. Besides, the social exclusion caused by the unacceptability of technology, climatic and environmental urgencies is also not being acknowledged or discussed at a local level. This exclusion hides climate data and model outputs, which explicitly show that the primary source of, for example, excess greenhouse gasses (GHG) is anthropogenic. International bodies like the Intergovernmental Panel on Climate Change (IPCC), have identified activities such as energy production, manufacturing, urban settlements, aviation, and transport are responsible for most of the GHG emissions that contribute to the rise of global temperatures. Despite such objective rationale, countries still struggle to work on behalf of their citizens—and citizens justifiably feel powerless and politically unrepresented. Sustainable development of the current polluted atmosphere requires inclusive and open discussion between academia, industry, government, and citizens.

According to Green et al., (2020), certain challenges faced by the researchers today consist of the time obligation to view and classify the data collected. Combining AI and CS is a possibility to advance efficiency and upsurge classification precision while simultaneously promoting the benefits lined with public employment and digital literacy. A significant example is Zooniverse (https://www.zooniverse.org) which is the chief platform for online citizen science hosting over 120 projects with 1.7 million registered applicants around the world (Trouille et al., 2019). According to Trouille et al., (2019), Zooniverse comprises of projects (e.g. Supernova Hunters project) which illustrate the additional power from merging human and machine classifications. Citizen-collected data are sometimes disapproved of being of lower accuracy or biased, which limits their use for various scientific purposes (Hecker, 2018). CS project leaders are accountable to control, measure and report data quality and the quality of the procedures involved, to demonstrate the validity and reliability of the data. Technology innovation can address the issues of data validation and verification in environmental monitoring. For further development of CS efforts, it is imperative to investigate these innovations in technology, that enables to reduce the current gap between citizen scientists and research scientists. ***Therefore, to address this gap, the study aims to assess different methods or technologies used in AI which can be applied to CS data.***

1.2 Problem Statement

Air pollution in Europe continues to persist, despite a substantial decrease in emissions inevitably, it continues to harm human health and the environment. A significant proportion resides in air pollution that poses health risk areas, for example, approximately 77% of city dwellers in Europe are exposed to fine particulate matter ($PM_{2.5}$), at levels considered injurious to health according to EEA, (2019). Table 1 shows the premature deaths attributable to $PM_{2.5}$, Nitrogen dioxide (NO_2) and O_3 exposure in the Netherlands, EU-28, and total EEA-33 in 2016. Premature deaths are considered to be preventable if their cause can be eliminated (EEA, 2019). AQ investigation and monitoring have become a thought-provoking issue, given the intricacy of the drivers of air quality pollutants which creates an urgent need for intelligent and adaptable models to address "non-linear and non-stationary behaviours of air quality at the near real-time horizon" (Sharma et al., 2020). RIVM predominantly focuses on the National Air Quality

Monitoring that also concludes that citizens are mainly interested in the local situation of air quality in their neighbourhoods.

Table 1: Premature deaths attributable to different air components, exposure in the Netherlands, EU-28 and total EEA-33 in 2016 (EEA 2019).

Country	Population (x1000)	Annual mean (PM2.5)	Premature deaths (PM2.5)	Annual mean (NO2)	Sum of Premature deaths NO2)	Somo35 (O3)	Sum of Premature deaths (O3)
Netherlands	16,979	11.3	9,200	20.5	1,500	2,428	270
EU-28	506,028	12.93	374,000	16.29	68,000	3,547.19	14,000
Netherlands	16,979	11.32	9,200	20.47	1,500	2,428.48	270
Total	538,014	14.42	412,000	16.28	71,000	3,811.00	15,100

'Hollandse Luchten' (Dutch Skies) is a citizen science project by Waag organization which involves citizens in measuring air quality in their environment in the Province of North Holland. This pilot project and its related study provide local communities of Noord-Holland with air pollution forecast. With this generated and analysed data, citizens can influence policymakers to regulate local and regional polluters and alert their communities accordingly. This is a collaborative approach for citizens to engage in understanding their environment. The project includes developed citizen sensing technologies and information platforms actively participated in CS networks. A vast number of affordable sensors around the Netherlands were deployed. To activate and empower citizens, in collaboration with the municipalities and RIVM, the effort of climate scientists facilitates bottom-up actions by equipping the citizens with tools and methods. CS is one of the main approaches contributing not only to climate awareness campaigns but also concrete actions and solutions. However, CS face a dilemma in relying on contributions from volunteers to achieve the required scientific goals. In terms of improving the quality and reliability of the data collected from the volunteers and for improving the accuracy of data analysis, AI methods or algorithms can be integrated into CS initiatives or AQ information systems. Such enhanced methods could facilitate improved citizen engagement to increase the quality of air pollution data.

From the brief description above, the study mainly focusses on two aspects, firstly, analysing the possible AI tools that can be beneficial for CS AQ data; and secondly, to evaluate the efficiency of citizen engagement through identifying the factors influencing AI integrated citizen participation. For this purpose, the case of the Hollandse Luchten pilot project will be analysed through a case study strategy.

1.3 The relevance of Research

With the interplay between citizens, local community cooperatives, and sustainability initiatives, civil society is emerging as a driving force in today's search for development and efforts towards creating more sustainable societies. It is not only imperative to provide citizens with tools to carry out such bottom-up initiatives, but also to ensure the reliability of the data collected by the citizens for research.

Citizens are often intrinsically motivated to try and create change and improve. Either they have an interest in the science or technology behind measuring (community of practice), or a relationship with the subject because of their circumstances (community of interest). This study is significant because citizens often bring extensive expertise; about neighborhoods, social dynamics, historical insights, or related ‘professional’ expertise. They understand the true urgency in their community but lack the scientific knowledge and interpretation and mitigation skills necessary to create valid sensing strategies. The main outcome of this objective *is a societal action* performed by citizens which will stand to inform policymaking. This creates social value, working parallel with the research scientists to make it possible to monitor AQ themselves, taking a bottom-up approach at a local level.

To overcome technical and social differences, this study aims to map existing tools and explore possibilities for integration of AI in CS to improve the data collected by the citizens. A unique example of such integration is *Gravity Spy* which combines human and machine classification, “leveraging human pattern recognition skills as a tool for image recognition and machine learning as a tool for systematic analysis of large datasets” (Zevin et al., 2017). This research explores in the following sections such significant ground-breaking, vigorous, self-adaptive and competent AI-based modelling opportunities, that can be supportive in CS AQ supervisory planning unified with urban and social development. This requires the assessment of AI tools and methods improving the quality of CS AQ data and information systems, and the factors influencing citizen engagement by assessment of the process of Hollandse Luchten pilot project in North Holland.

1.4 Research Objectives

The core objective of the research is to explore AI methods to enhance the quality of CS AQ data, to explain the factors influencing the integration of AI tools and CS initiatives for AQ assessment in the case of Hollandse Luchten pilot project and to draw conclusions that can enhance the implementation of the project. Therefore, the specific objectives are:

- To explore the possibilities of AI to improve the quality of CS AQ data and information systems
- To explain the factors influencing the relationship between AI and the quality of CS AQ data
- To determine the extent to which the factors influence the relationship between AI and the quality of CS AQ data

1.5 Research Questions

To accomplish the research objectives, the main research question is:

Under which conditions does the use of artificial intelligence facilitate the improvement of Citizen Science air quality data in North-Holland?

To answer the main question, the following sub-questions are formulated:

- Which AI methods are advantageous/beneficial for improving the quality of CS AQ data and information systems?
- Which factors stimulate or hamper AI integrated CS for AQ assessment?
- How and to what extent do these factors impact the AI integrated CS for AQ assessment?

Chapter 2: Literature review/theory

2.1 Introduction

This chapter reviews the concepts of AI, CS, and AQ data and information systems to contribute literature knowledge to the main question and the sub-questions. The chapter refers to the literature which explores the definitions, principles, and capabilities of AI. It assesses the current AI methods used in advancing CS AQ monitoring methods by focussing on empirical examples and explains the relevance of CS. Furthermore, this chapter includes the concept of a socio-technical environment and elaborates the relationship between the concepts, and its influence on CS and AI technology. Finally, the chapter concludes with the explanation of conceptual framework, that exemplifies all concepts related to the improving the quality of CS AQ data with the integration of AI and its association to the socio-technical environment that has a crucial influence on the efficiency of CS.

2.2 State of the art of the theories/concepts of study

2.2.1 AI

According to the European Commission's (2019), Communication on AI[1], "Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans[2]. AI after been given a complex goal, act in the physical or digital dimension by perceiving the environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information. Results are derived from this data by deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions".

The three main capabilities of an AI system include perception, reasoning/decision making and actuation, "which can be categorized into two main groups that refer to the capability of reasoning and learning[3]". Reasoning techniques include knowledge representation, planning, scheduling, search, optimization that allow performing the reasoning on data retrieved from the sensors (Hleg, 2019). Learning, techniques, on the other hand, include ML, deep learning, neural networks, decision trees etc. that enable the AI system to learn to solve difficulties that cannot be precisely detailed, or "whose solution method cannot be described by symbolic reasoning rules" (Hleg, 2019).
While contributing to great opportunities, AI systems also embrace certain risks that must be addressed appropriately to ensure that the socio-technical environments in which these are embedded can be proven advantageous to the common good (Hleg, 2019). *Trustworthy AI* is, therefore, an ambition that is identified to safeguard the trust of societies, communities,

[1] "Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions on Artificial Intelligence for Europe, Brussels, 25.4.2018 COM (2018) 237 final."

[2] Humans design AI systems directly, but they may also use AI techniques to optimise their design" (Smuha, 2019)

[3] In this regard, see *A definition of AI – Main Capabilities and Disciplines*, published by the High-Level Expert Group on AI on 8 April 2019, accessible at: https://ec.europa.eu/digital-singlemarket/en/news/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines

economies and sustainable development in the context of rapid technological change (Hleg, 2019).

To implement the vision that was set by the European Commission for AI, the commission established the High-Level Expert Group on AI (AI HLEG), a group that was mandated of drafting the guidelines for Trustworthy AI, which is a prerequisite for people and society to develop, deploy and use AI systems (Hleg, 2019). The application of these principles is contextual and varies concerning the different occupations that AI methods and tools are used for. ***This study will focus on the possible AI methods and tools that can be used to enhance the quality of data analysis and the information systems in CS AQ assessment considering the in-context principles of Trustworthy AI.***

2.2.2 AI integrated CS Initiatives

Citizen Science

Citizen Science enables citizens without any professional scientific experience to utilize technical tools to discover questions that concern them. An informed contribution can be made through public debates from the learnings through engagement and developing ownership of current existing issues. EEA, (2020, p.7) defines citizen science both as “science which assists the needs and concerns of citizens and as a form of science developed and enacted by the citizens themselves”.

Green, et al., (2020) elaborates the processes involved in citizen science that include: i) Contributory, where the public principally enlarge data to the projects premeditated by researchers; ii) Collaborative, where the community contributes data but then may also help to enhance venture design, analyses data, or distribute findings; (iii) Co-created when public participants are enthusiastically involved in most of the process (Bonney, et. al. 2009); iv) Contractual projects, where community pursues professional researchers to operate a detailed enquiry; v) Collegial contributions, where non-credentialed entities have directed autonomous research, documented to some extent by institutionalized science (Shirk, et. al. 2012); vi) a grouping in which and all phases of fabrication is approved by the general public and the procedure does not involve professionals at any stage (Roy, et. al 2012).

Green, et al., (2020) also identifies the potential advantages of community participation in these projects. Citizen participation builds a sense of inclusion through capacity building. The author argues that community engagement in scientific research also increases the knowledge and skills that allow these communities to have a sense of purpose. For example, involvement in conservation-based citizen science enables participation of citizens of all ages and creates their link to nature which is also beneficial for mental and physical health. CS processes also reduce ‘extinction of experience’ that lessen the disconnection with nature and community-related issues (Soga, 2016).

Current Applications of AI in CS

Ceccaroni, (2019) argues that ethical guidelines of AI should not only be applied to other fields but also be explored carefully applied in context to CS. Having said that, current AI applications comprise of automated reasoning with ML which helps to generate programs that allow computers to reason automatically. Through deep learning identifying objects or categorizing digital imagery can be an effective and efficient technique (Ceccaroni, 2019). Another application is called computer vision and hearing, that explores how computer systems can classify, identify or understand high-level understanding from digital images, videos or audio recordings, which is commonly used in CS (Ceccaroni, 2019). Furthermore, knowledge representation is another significant field of AI that can help assess environmental impacts. There are several organizations like US Citizen Science Association's (CSA), that work on the development of the representation of data and metadata in CS (Ceccaroni, 2019). Contributions in the field have also been made by organizations like European Citizen Science Association (ECSA), and the Australian Citizen Science Association (ACSA) regarding addressing the definition of interoperability, reusability and compatibility in CS (Ceccaroni, 2019).

2.2.3 CS AQ Information Systems

AQ Data

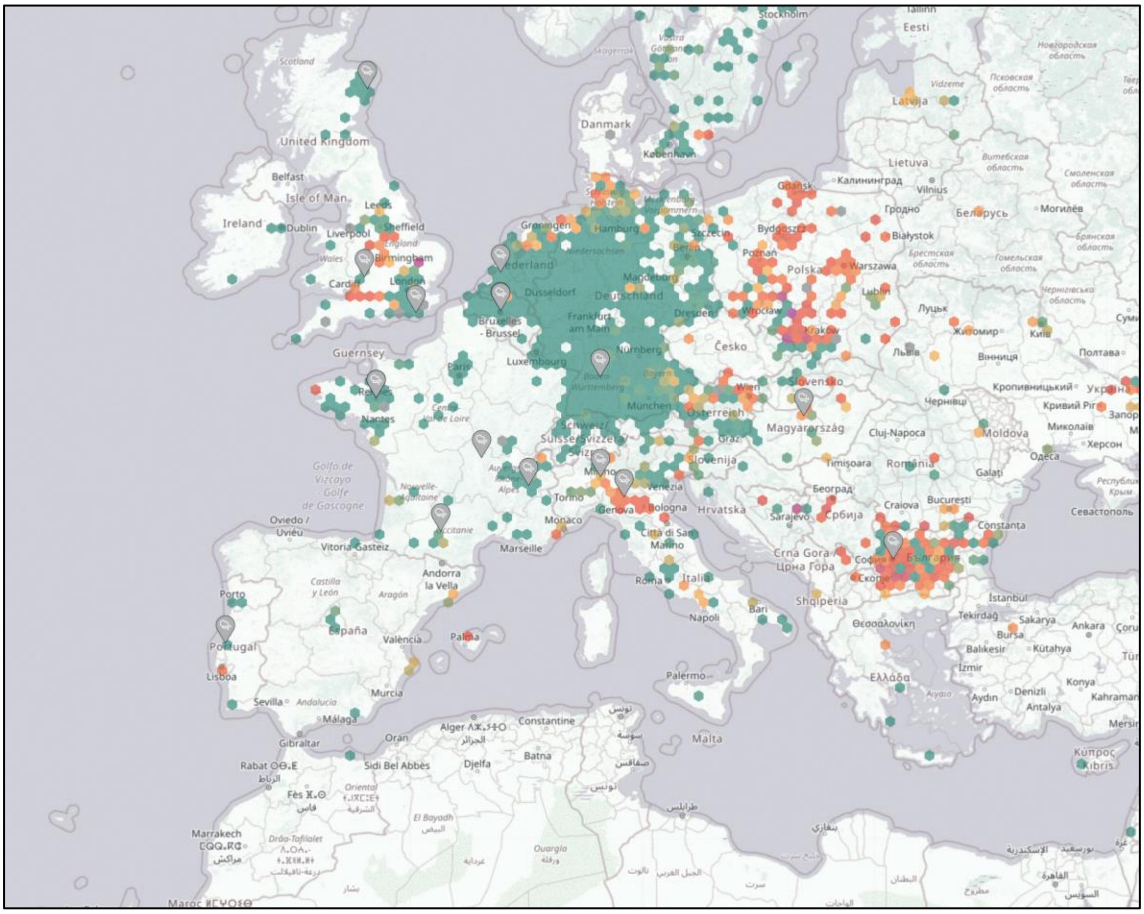
AQ data constitutes of six major air pollutants that have been designated by U.S. Environmental Protection Agency (EPA) as 'criteria' pollutants, which label these pollutants as the indicators of overall AQ namely, carbon monoxide (CO), nitrogen oxide (NO_2), sulphur dioxide (SO_2), ozone O_3, particulate matter (PM) and lead (Pb). The principal component of air pollution is PM which is studied worldwide to minimalize the effects of air pollution or prevent the effects via real-time anticipating networks viewing early warnings (Sharma; Deo, et al., 2020). $PM_{2.5}$, (2.5 micrometres or less in diameter) and PM_{10} (10 micrometres or less in diameter), are the major atmospheric variables which accompany increased respiratory induced mortality, recurrent health-cost and cause lower atmospheric visibility (Sharma et al., 2020). Long-term expose to ambient PM has also an immense impact on morbidity and mortality which makes it a primitive variable to be addressed due to the rising health issues. Premature deaths in the Netherlands are approximately 16,979 attributable to $PM_{2.5}$, O_3, and NO_2 in 2016 according to air pollution country factsheet data by the European Environment Agency (EEA). There is an urgent need for versatile models to address the non-linear and non-stationary conduct of air-quality at near real-time to provide hourly forecasts information for the use of the general public (Sharma et al., 2020).

CS AQ monitoring with low-cost devices

According to CEN, (2019) and Lewis et al. (2018), CS initiatives with an emphasis on AQ generally use low-cost measuring devices to explore more about local or regional air pollution and its sources. There are different types of instruments for measuring air quality, namely; 1) *a passive air pollutant sampler* which consists of a 'plate' exposed to the air to collect settled air pollutants from the plate, which is further analyzed in a laboratory; 2) a *low-cost air pollution sensor device* measures certain pollutant in the ambient air in real-time, for example, gas or particle concentrations are usually observed as electrical signals, which are converted to a concentration value by data acquisition software; 3) *an air pollution sensor system* which consists of a grouping of one or more sensors with a power source and usually a processor that converts the optical signals into concentration units, which is further deployed individually or in a group by the user; and 4) an air pollution *reference instrument* usually used by public authorities officially used in AQ monitoring networks for purposes like regulatory compliance checking.

According to EEA Report 2020, *Sensor.Community* is a 'grassroots' air quality initiative which uses citizen science to gather large air quality data sets by making PM visible by focusing on the areas where the concentrations are not officially measured, and by picturing the results in online viewers (Figure 1). The initiative started at the local level in Stuttgart, and from there, the project has full-fledged to capture measurements from over 10,500 unique locations around the world (in 71 countries). However, the Sensor.Community (2020) acknowledges the limitations of the accuracy of the data provided by the sensors. The results are robust when the co-location measurements are compared with the results obtained from a more advance optical monitor, under typical conditions, that is when the humidity and the PM concentrations are low. However, high humidity, for instance, in the case of fog, the sensors can deliver incorrect values. Therefore, the initiative is looking for algorithms that can minimize the impact of high humidity on PM concentration data.

Figure 1: Screenshot of Sensor.Community[4] map_displaying results of measurements results of particulate matter. Source: Sensor.Community 2020.



Calibrating sensor systems through AI

The EEA (2020), report further explains the necessity to ensure the quality and reliability of low-cost measuring devices through calibration. Options for calibrating sensor systems, out of which one of the methods is ML. ML is an approach used in the rapidly developing field of AI. ML is a study of computer algorithms which are used to automatically acquire, and advance performance based on experience, and "algorithms are a sequence of instructions and rules designed to solve a particular problem" (EEA, 2020, p.45). ML can range from statistical models to artificial neural networks. These are computing structures that are inspired by the

[4] **Note:** "Information on colour coding and its interpretation is available on the Sensor.Community map viewer. When individuals contribute their measurements to open data networks, privacy issues must be considered. On Sensor.Community's data platform, sensor data cannot be traced back to the precise within each hexagon (because of the limited zooming function)".

biological neural networks that institute animals' brain. The ML technique applied to CS considers several variables that enable the system to interpret the meteorology on sensor measurements and as well as interference from other gases. When sensors are calibrated against each other, ML produces a statistical analysis of data from across sensor systems, the results of which are compared against the official monitoring stations equipped with reference instruments (EEA report, 2020).

Optimization of geographical measurement location through AI

According to Gupta et al., (2018), because of economic constraints and the limited monitoring sensors in cities, the accurate assessment of intra-urban variability of air pollution is also inadequate. Moreover, due to the high spatiotemporal variability, interpretation of the sources from where the emissions originate, disperse, and chemically transform, becomes challenging. Spatial coverage of air pollution monitoring networks needs to be accounted for improved comprehension of exposure in microenvironments, which simply implies that unfitting location choice may contribute to over-or underestimation of pollutants instigated from numerous emission sources in the city. Exploration of the potential of small and low-cost air quality monitoring sensors have been a prevalent topic for various citizens and environmental agencies (Gupta, et al., 2018). Previous studies suggest that serious data gaps and irregular measurements, regarding data quality and identifying the origin of the emission source are incurred because of low-cost sensors. These are mainly gathered with the help of community participation. Optimizing the monitoring locations is, therefore, considered desirable to capture spatial variability, especially because of the involvement of specific cost and time (Gupta, et al., 2018). This simply means that it is essential to identify the optimal placement of monitoring stations to reach the maximum efficiency in integrating advanced sensor technology with CS efforts. Gupta (2018) proposes an optimization method that includes identification of advantageous spread and optimal monitoring site locations to minimize mean predictive error for land-use regression (LUR) estimations of AQ parameters.

Large spatial coverage is required for climate change studies, whereas higher spatial resolution is a prerequisite for human exposure studies. This includes a thorough depiction of air pollutants in spatial gradient (Tao; Xing, et al., 2020). High-resolution AQ simulations become possible because of the development of the urban land scheme, satellite retrievable datasets and super-computing technology, thereby, improving the accuracy of prediction of the meteorological settings and pollution spatial dispersal. (Tao; Xing, et al., 2020). Thus, (Tao; Xing, et al., 2020) uses a high-resolution AQ model to examine the effect of resolution on the simulation of O_3 and $PM_{2.5}$ concentrations and accompanying population contacts in Beijing, China. For this purpose, enhancements in emissions inventory are made, with 1km by 1km horizontal resolution and Land Use and Land Cover (LULC) data, that describe vegetation, water, natural surface, and cultural features on the land surface (Tao; Xing, et al., 2020).

To conclude, the literature review suggests significant use of AI methods, that can be integrated with AQ data and information systems to enhance the quality of the data, however, with citizens involved, other factors can influence this relationship.

2.2.4 Factors Influencing CS

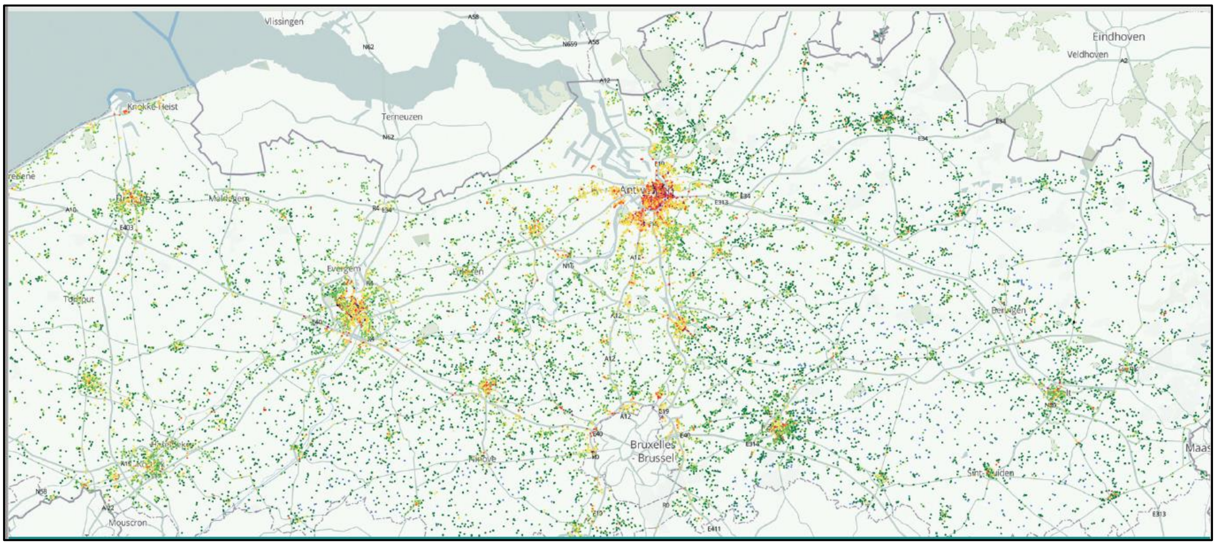
The above section summarizes the academic evidence of possible AI methods and tools that can enhance CS AQ data and information systems. However, for the AI integrated CS for AQ assessment, certain factors influencing citizen's voluntary engagement in projects like Hollandse Luchten pilot (case study) also needs to be analysed. Assessing these factors shall determine the engagement process and motivations of communities which shall have an impact on the efficiency of these citizen-led initiatives. This section describes the significant social and technical factors affecting community participation by reviewing empirical CS projects across Europe.

The technologically driven citizen science characterizes a low-cost mode to reinforce the infrastructure for science while simultaneously engaging community participants in science. Citizen Science is grounded on two-pillars – technological and social systems. Technological systems are required to manage huge amounts of circulated resources (McCrory et al., 2017). According to (Purwanto et al., 2020b) technological factors concern integration and interoperability with existing systems, an interactive feature of platforms, security and standardization, and the use of emergent technologies. Additionally, poor quality of data (technological factor), may also hinder the participation of citizens' in CS, therefore making it necessary for the organizations to maintain data quality (Purwanto, et al., 2020b). Social factors affecting citizen participation are motivations and individual conditions (Purwanto et al., 2020b).

Example of Curieuze Neuzen Vlaanderen

According to EEA, 2020, Curieuze Neuzen Vlaanderen (Curious Noses Flanders) initiative was implemented in 2018, by Flanders Environment Agency in collaboration with the University of Antwerp and the initiative was tagged as 'the largest CS project on AQ to date'. Flemish citizens used a standardized measurement device, a passive sampler, for the measurement of NO_2 concentrations. This was further developed in a detailed spatial map (Figure 2), that also aimed to improve the predictive competence of the existing AQ in Flanders.

Figure 2: **Screenshot of the map showing the results of the Curieuze Neuzen Vlaanderen**[5] **NO2 measurements.** Source: Curieuze Neuzen Vlaanderen 2019



This would indeed provide a precise estimate of the citizens' exposure to NO_2. This will also determine public health effects as a source for making recommendations to policymakers. Furthermore, the project partners engrossed almost 53,000 people interested in participating in

[5] **Note:** Information on colour coding and its interpretation is available on the CurieuzeNeuzen map viewer.

the project out of which 20,000 were selected, to measure AQ during May 2018. The report also mentioned that Curieuze Neuzen Vlaanderen not only was successful in collecting high-quality large-scale data but was also helpful in raising awareness of AQ issues among the participants. In addition to this, the initial results were regulated to official reference monitoring stations, and a 23-month average was calculated that allowed the citizens to compare the measurements to the official EU limit values and WHO guidelines (EEA, 2020). Moreover, the report also explains that Curieuze Neuzen Vlaanderen also observed behavioural changes in terms of choice of transport mode in three groups of participants; 20,000 participants in the AQ measurement campaign, 33,000 people who expressed interest in the project but were not selected, and a reference group of 1000 citizens that were not involved in the project. Interestingly, most people that were involved and interested in the project were using their cars less, and the ones who were not interested in the initiative did not change their behaviour.

CS Engagement mechanisms in AQ investigations

CS environmental data is collected at unique scales and speeds addressing diverse societal problems. This also includes the participation of various stakeholders. However, the way citizens are involved in these CS projects is not analysed and evaluated. Therefore, several engagement mechanisms are identified by reviewing ongoing EU-CS projects investigating AQ. McCrory, et al., (2017) identifies engagement mechanisms in existing air pollution CS projects. and argues that several mechanisms emerge at the interface between AQ measurement, CS and knowledge production. These are Scale, User-involvement, Communication and User-motivation.

Various AQ monitoring projects like 1) EveryAware APIC, 2) Urban AirQ, 3) CITI-Sense, 4) iSPEX, 5) SecondNose and 6) ClairCity, suggests that in the expansion of CS initiatives, the inclination towards ICT technologies is often proved as a catalyst. For example, iSPEX achieved immense participation in terms of data collection, however, it also faced challenges in terms of replicating the project from EU, due to their technical and institutional inabilities. This determines a scaling issue, which is especially related to spatial, temporal or institutional scales. Co-creation is a rapidly gaining popularity as a concept that potentially addresses often exclusive nature of digital literacy. “Such exclusion can result in minimal user input regarding the user interface, the usability of the platform, look and feel of the sensor and user concerns”(McCrory, et al., 2017). Citi-sense, UrbanAirQ, and Second Nose projects encouraged co-creation as integration methods and suggest that beyond the traditional forms of knowledge and practice, other socio-technical factors need to be examined (McCrory et al., 2017).

Another significant finding highlights the importance of communication in CS projects on multiple levels. For example, users were directly able to access data measurements from web applications for UrbanAirQ and CITI-SENSE, whereas iSPEX uses and analyses mobile images as proxies for outdoor air pollution. Qualitative insights also suggested the positive response of users to a visible company of academia, specifically for processes such as “data quality, acknowledgement of contributions, translating input into impact, and offering support”(McCrory, 2017).

In addition to this, the findings also suggest that identified motivations in AQ monitoring are diverse, ranging from curiosity, interest in contributing to science and interest in local pollution, to using data to inform policy-making and encourage new forms of governance (Land-Zandstra, 2016; Leonardi et al., 2014). Behavioral studies conducted as a part of EveryAware project found that users were drawn to high-polluted areas rather than avoiding the polluted hotspots because of their motivation of providing to technology, and curiosity in the precision of the sensors (Sirbu et al., 2016).

Social Factors: Motivations and Behavior Change

Recognized motivations and expectations for operators of air pollution sensors are highly diverse, ranging from curiosity, interest in local pollution, to informing policymaking and encouraging new forms of governance. Motivation can be characterized by intrinsic and extrinsic motivation (Purwanto et al., 2018a). Examples of intrinsic motivations include personal interests that are compatible with the individual's values (Weerakkody et al., 2017a). For example, contributing to the benefit of the community (Purwanto et al., 2018a; Kuk, 2011). On the other hand, examples of extrinsic motivations include prospects of financial improvements or future employment (Kuk, 2011). Moreover, individual conditions are also identified as social factors influencing citizen engagement. These individual conditions include resources like internet access, time, and money, for engaging in CS. Furthermore, influence from social relationships, particularly seniors or teachers (in the case of students) or peers (social media), is found imperative in affecting peoples' intentions or their decision as a participant (Purwanto et al., 2018a).

Participation Cycle

Yadav and Darlington, (2016) analyze a volunteer's participation cycle in a CS project (Figure 3).

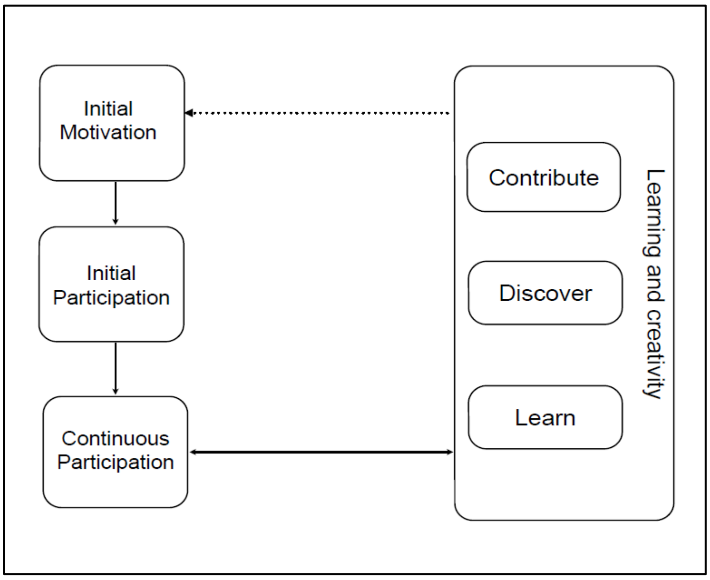


Figure 3: Volunteer's participation cycle in a Citizen Cyber Science Project. Source: Yadav and Darlington, 2016

The initial motivations are based on 1) willingness to contribute to science; 2) the willingness to learn; 3) for fun and enjoyment through game playing or other interestingly interactive projects (Tweddle et al., 2012; Nov et al., 2011). The Initial participation is based on; 1) easy access to interesting CS projects; 2) simplicity of launching the project 3) quick, easy, and secure initial setup (in case of projects other than cyber projects, this could be related to secure data and privacy) (Yadav and Darlington, 2016). Continuous participation or long-term engagements depends on 1) receiving feedback in terms of appreciation for their participation (Jennett and Cox, 2014) 2) ability to measure the learning while participating in the project; 3) project meeting volunteers' fun or enjoyment expectations (Jackson et al., 2015).

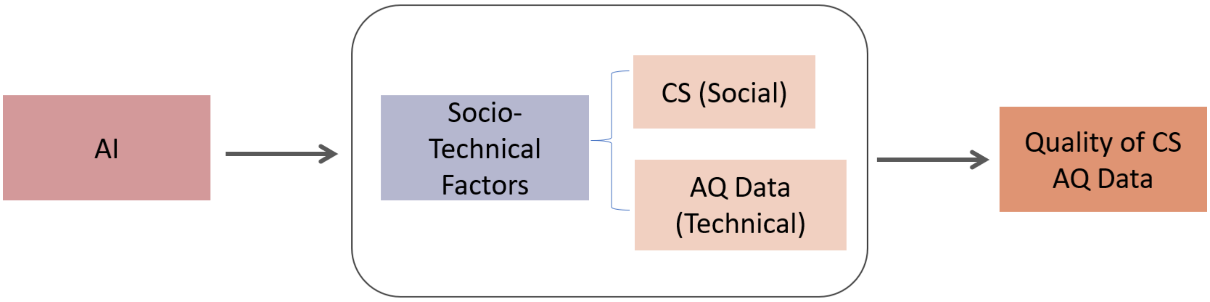
To conclude, the socio-technical factors presented in this chapter confirm the direct and indirect influence on the process of CS AQ monitoring. To improve the process of CS AQ projects, the importance of socio-technical factors needs immense attention.

2.3 Conceptual Framework

From the literature review above, the theoretical framework guiding this research is based on two main variables: "AI", as an independent variable and "Quality of CS AQ data" as a dependent variable. This is illustrated in Figure 4, which is supportive to the main question and the sub-questions. The objective of the study is to design an AI integrated method for improving the quality of CS AQ data, which is also a desired outcome in this study. This makes the quality of CS AQ data a crucial variable in this study that has a causal relationship with AI.

CS being the context of the study, the literature review also indicates that socio-technical factors affecting citizen participation will act as a mediating variable for the quality of CS AQ data. As a mediating variable, the socio-technical factors also influence the integration of AI. To address the opportunities and risks associated with the implementation of the AI-enhanced CS AQ data, the socio-technical factors need to be assessed in-depth, as these factors mediate the relationship between the independent and the dependent variable.

Figure 4: Core Conceptual Framework: The relationship between the independent variable, AI and dependent. Source: Author, 2020



To investigate the integration of AI methods, two aspects were considered. One was the process of the CS AQ project, in this case, the process of Hollandse Luchten pilot, the other is the social impact and technical robustness of AI, derived from the Trustworthy principles of AI. The variables are selected with the consideration of the in-context application of AI.

To investigate the social-technical factors affecting citizen participation, that act as the mediating variable, the social factors, consisting of citizens' participation and behaviour, citizens' perceptions, and Individual conditions will be analysed. Additionally, information systems, also referred to as the technical factors are examined, as these directly or indirectly affect the social factors affecting citizen participation. These sub-variables are mostly derived from the literature review to explain the social-technical factors (explained in Chapter 2).

The expected result or output of this study is the improved quality of CS AQ data by integrating AI methods. To investigate this, the quality of data (the results) from Hollandse Luchten pilots are analysed.

To conclude, the conceptual framework illustrates how to 1) explain the relationships between the factors affecting the performance of AI integrated CS AQ data and 2) develop the casual relationships between the concepts of AI CS and AQ data. Therefore, AI is acting as an independent variable and the quality of CS AQ data is the dependent variable. As this causal relationship is affected by socio-technical factors, these factors are collected in the mediating variable in the research. This conceptual framework will guide the empirical research process from data collection to analysis as described in Chapter 3.

Chapter 3: Research design, methods, and limitations

3.1 Description of the research design and methods

3.1.1 Introduction

There exists a considerable body of literature explaining the efficiency of CS initiatives integrated with the various AI methods. The types of AI methods and the associated opportunities and risks will be analysed. The literature review also reveals various factors that influence this integration process. These factors include aspects that affect citizen participation. To answer the main research question and the sub-questions, this section details out the operationalisation of AI and the quality of CS AQ data, including their causal relationship which is mediated by socio-technical factors. This chapter elaborates on the research design and methods, operationalization of the variables, the indicators and the potential limitations and challenges used in the study to respond to each of the sub-questions.

3.1.2 Research Strategy

The research objective is to disclose and elucidate the factors that influence the improvement of CS AQ data through the integration of AI methods for Hollandse Luchten observations performed in the province North-Holland. Through the literature review, different methods of AI integrated to improve the quality of CS AQ data have been explained. The literature review also divulges the most influencing factors, that is, the socio-technical factors and the principles of AI that needs to be assessed in depth. ***Thus, the research is both exploratory and explanatory, as part of the study aims to explore the possible AI methods to enhance CS AQ data, and on the hand, the study aims to explain the factors affecting the quality of CS AQ data.***

For this purpose, the *Case Study* research strategy is used, as it develops a detailed qualitative study within the contexts. The objects of the case study, Hollandse Luchten is based on constructive CS networks which are conforming to most of the CS networks in the Netherlands, thereby having a representative character for the Netherlands. Studying this case will enable valuable insights and in-depth understanding of the concepts in the empirical and practical context. Consequently, theories can be compared, and the causality of factors can be explained through a case study. Finally, the amalgamation of primary and secondary data collection and mixed method of analysis enriches and advances the qualitative research.

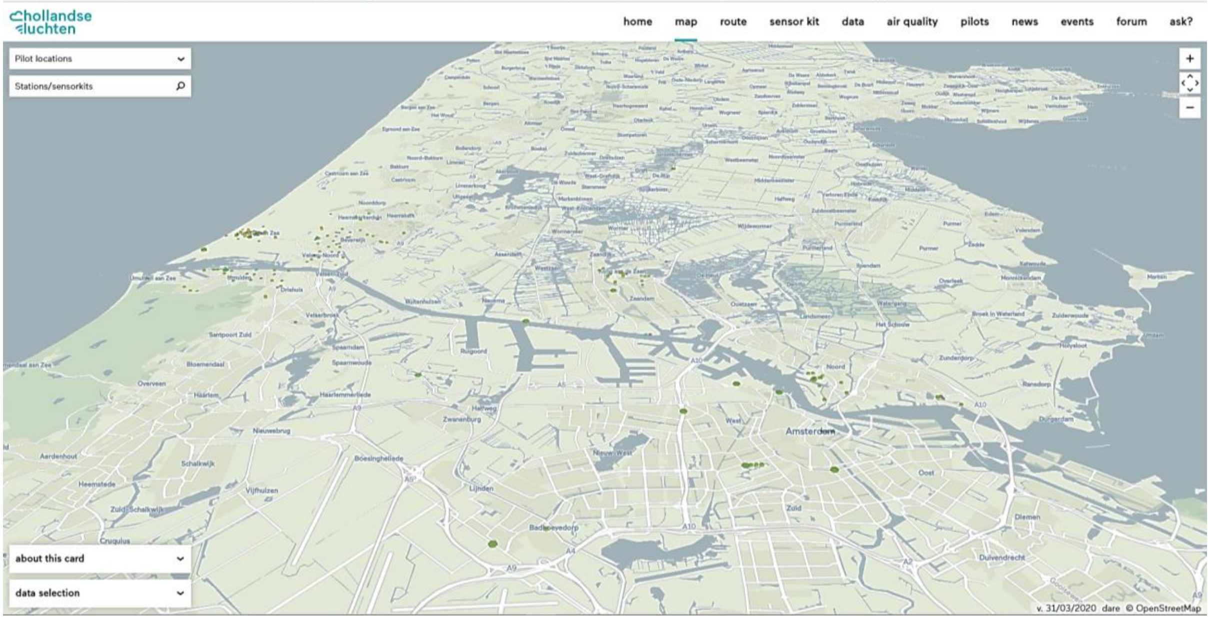
3.1.3 Description of the case

Hollandse Luchten Project

In the Hollandse Luchten project, residents of the province of Noord-Holland themselves measure the quality of the air using affordable measuring sensors. The measurement results are published as open data. Hollandse Luchten is investigating a new way of measuring air quality from the perspective of the resident. Analyzing the results together with experts creates a shared picture of the situation. For example, the province wants to lay the foundation for a discussion about the causes of air pollution and possible solutions. The Hollandse Luchten project has started in the IJmond region (Wijk aan Zee, Beverwijk, IJmuiden and Velsen). This region is the biggest and most urgent pilot location. Here, citizens have been concerned with air quality and their health for decades, but due to recent graphite 'rains' in the autumn of 2018, the concerns skyrocketed. The project builds upon previous experiences that use the citizen sensing framework through which we take citizens through each step of the sensing process.

By using this framework, the sensor becomes a mean that ***can empower citizens to contribute to the change*** that they would like to see in their neighborhood. In the province of North-Holland, 200 sensors will be deployed in three pilot locations (see figure 5).

Figure 5: Hollandse Luchten map showing sensor stations across the pilots. Source: Waag, 2020



Furthermore, measurements are carried out in the North Sea Canal area, near Zaandam and Amsterdam-Noord. Most sensors measure particulate matter (PM2.5 and PM10). Besides, several sensors measure nitrogen oxide and ozone. Where the particulate matter is particularly important in the IJmond, due to the emission of Tata Steel, in Zaanstad and Amsterdam-Noord it is mainly nitrogen dioxide caused by traffic. The participants' measurement network and the measurement results can be seen directly by everyone on the Hollandse Luchten website. Also, for interested parties who do not participate in this project themselves. Each meter has its number so that participants can monitor the performance of 'their' sensor. The map (figure 7) also shows the data from the official, national air monitoring network of RIVM and GGD. Since the integration of AI with CS AQ data is a relatively new phenomenon, the empirical cases are limited, because of which Waag's case is selected, as Waag is also working on AI methods for the society.

3.1.4 Research Methodology

Qualitative data through both *primary data* (semi-structured interviews, refer Annex 1), *and secondary data* through *desk research (*online databases, official websites and published articles, newsletter, frequently asked questions), was collected and used to facilitate a holistic understanding of the phenomenon being studied.

Primary qualitative data collected examines the case study and provides with in-depth knowledge in comprehending the answers to the research questions, as it pledges the reliability of data sources.

The collection and analysis of secondary qualitative data were used to triangulate with the primary data collected from the semi-structured interviews. Secondary sources comprising of data, through various online databases: official websites of the pilot (Hollandse Luchten), and official government websites (RIVM, Province of North Holland, GGD Amsterdam), enables to aid the current trends and implementation of the pilot project. These also help to set the scope of the research, which permits a more concise and focused study. Moreover, secondary qualitative data (research findings from an online survey conducted by the Waag) was analysed to support the findings from the primary data collection method.

3.1.5 Sample Size and Selection

To assess the potential of AI, it is necessary to collect primary data through experts in the field. For this purpose, the *purposive selection* of the sample is done. The objective of the research is aligned with adding a layer of AI to the ongoing CS AQ pilot projects like the Hollandse Luchten project. Waag as an organization is associated with the projects and is already working on AI for Society. This initiative contributes to a safe, and democratic implementation of AI, in which the interests of citizens are central. Therefore, semi-structured interviews with experts from Waag will be commissioned in combination with the citizens who have participated in the CS AQ projects.

To measure the possibility of AI methods, an AI expert from Sobolt was approached. In addition to this, to assess the factors affecting CS and quality of CS AQ data, experts from RIVM, Royal Netherlands Meteorological Institute (Koninklijk Nederlands Meteorologisch Instituut (KNMI), GGD Amsterdam and Province of Noord Holland and Waag were interviewed. Because of the limited time and budget, not all participants of the total population (200 measurement station owners) were interviewed, thus, key informants representing the population of the Hollandse Luchten project are selected. A snowball sampling was chosen in the study, with the respondents recommending contacts with more potential respondents.

Regarding the selection of respondents, as mentioned in the previous section, a triangulation method, secondary data collection, especially from the source (official websites and newsletters) was used to help in the identification of the respondents, targeting those, who were officially involved in the pilot. Because of the privacy policy of the organizations, the citizens' scientists' names were not revealed, because of which, interviewing the citizens was not possible, however, the Hollandse Helde (Dutch Heroes), who acted as a mediator between the organizations and the citizens were revealed by some experts. Out of the 10 citizens (citizen scientists) that were approached, 2 Dutch Heroes were willing to be interviewed for this research. From the interviewees, snowballing was used to get more respondents, including experts and citizens.

This would provide a heterogeneous sample of 11 (see Table 2) through purposive sampling, comprising of 9 experts and 2 citizens were interviewed. This determines the sample selection method for primary data collection. Semi-structured/in-depth interviews require a minimum sample size of between 5 and 25 (Cresswell, 2007)

Table 2: Respondents (Experts, Citizens, Stakeholder). Source: Author, 2020

Code	Respondent's description	Position	Interview Duration (mins)
EX1	The expert from Waag, working on AI for Society, Hollandse Luchten and Sentinel Citizen	Data protection officer	50
EX2	The expert from KNMI	Data Scientist	42
EX3	The expert from GGD	Data convener	41
EX4	The expert from Waag, working on Hollandse Luchten project	Head of Communications	31

EX5	The intern from Waag, working on Hollandse Luchten project	Intern for impact analysis	25
EX6	The expert from RIVM working on air quality and Hollandse Luchten	Air Quality Specialist	55
EX7	The expert from Sobolt working on AI	Head of AI toolbox	33
EX8	The expert from Province of Noord Holland	Environmental Lead	35
EX9	The expert from Province of Noord Holland	Data Scientist	25
CS1	Hollandse Helde or Dutch (Netherlands) Hero (Buiksloterham)	Community Leader and Technical Analyst	40
CS2	Hollandse Helde or Dutch (Netherlands) Hero (Buiksloterham)	Community Leader	35

3.1.6 Data Collection Instruments

Primary data: Primary data related to the potentials of AI is collected through *semi-structured interviews research instruments*, which were recorded with the key informants and experts from the field. A noteworthy aspect is the potential of AI is measured through technical and social indicators (see Table 3) which are used in the framing of the questionnaire (Refer Annex 1). This will be the first phase of the interview. The second phase of the interview with the experts will have questions about the socio-technical factors affecting CS.

The respondents participating in CS projects (Hollandse Luchten project) will also provide data through the same method, mainly concerning the socio-technical factors. The questions regarding social factors mainly include the citizens' participation and behaviour, citizens' perceptions and individual conditions (see Table 4) that will enable the researcher to explain the reasons for community engagement. Then, questions regarding the technical factors including the information systems (see Table 4), will explain the relationship of the factors in-depth. Additionally, stakeholders involved in the Hollandse Luchten project from RIVM, GGD, Province of North Holland, besides with KNMI, were interviewed, to assess the quality of the data, which are the results of the Hollandse Luchten pilots (See Table 5).

Data will be collected through supervision of questionnaires. Respondents will be allowed to answer the structured questions and will be allowed to provide with additional information wherever possible. Thus, semi-structured interviews guarantee reliable qualitative data as it provides the respondents with freedom and flexibility to express their valuable opinions (Creswell, et al., 2004; Cohen, 2006).

Secondary Data: Typical sources included for secondary data collection are data from through various online databases: official websites of the pilot (Hollandse Luchten), official government websites (RIVM, Province of North Holland, GGD Amsterdam), social media (Youtube, Meetup). For triangulation, the primary data that is collected through the interviews comprising the project information is cross-referenced with the secondary data. Additionally, the research findings from the survey conducted by Waag in collaboration with the Province of North Holland will also be used for triangulation of data sources.

3.1.7 Data Analysis Techniques

The qualitative data was composed through semi-structured interviews, that were recorded with the permission of the respondents. The interviews were conducted through online mediums with the help of online meeting applications. This technique enables systematic documentation of audios and enables better focus on the discussions and interactions with the interviewee. Subsequently, the researcher manually transcribed the entire interview, simultaneously highlighting the chief concepts. The next step was the coding process, which includes labelling the appropriate words, phrases, sections.

Qualitative data processing software[6] is used for interview analysis, which on one hand, reduces the potential of errors because of the consistency and transparency of the analysis procedure, and on the other hand, allows to simultaneously explore other research materials (Ngalande and Mkwinda, 2014).

After the transcription of the interviews was coded, three tools were used for the data analysis: Co-occurrence Table, Query Tool, and the Network Tool. The Co-occurrence Table displays a record of numbers or co-occurrences, amongst the combination of codes occurring in a quotation. However, it is important to highlight that, the tools work, that is the quotations are counted only when the respondent mentions the two indicators (or codes) at the same time. If they mention about both subjects, but separately, for instance, in different interview questions, it will not appear on the co-occurrence tool. Besides, the co-occurrence table is a stimulating tool for the data analysis, that also helps to establish the initial relationships between sub-variables (in this case). The next stage for data analysis was the application of the Query Tool, which examine the relationship between codes, permitting the researcher to cross-examine by codes or code groups across documents. Network tool helps to build relationships between codes by implementing the type of relationships one code has with another. Reports were generated sub-variable wise to show what each code group (sub-variables) included during the interviews by the experts and the citizens. These outputs were further investigated by the researcher. Finally, findings were interpreted by the researcher and results, conclusions and recommendations were written, which will be presented in the following chapters.

Secondary Data Analysis includes the analysis of data from articles and online websites of the pilot projects, RIVM and KNMI data repositories. The content analysis technique is used to emphasise on the timeline of the project and the events that occurred during the one year of the pilot project. Significant Documents were selected and analysed conforming to the specific indicators (see Table 4,5,6). The content of the secondary data was coded in a similar way as the primary data using the same tools of the software. The research findings of the survey conducted by Waag was also coded in the software. This helped the researcher to concretise the findings of the primary data.

3.2 Operationalization: Variables, Indicators

As stated in Chapter 2, to achieve the desired outcome of improved AI integrated CS AQ data, the potential of AI, and the factors influencing CS for assessment of AQ data of the pilot project Hollandse Luchten needs to be analysed.

The contribution of AI can be measured by assessing the possible models of AI useful for CS and AQ data and information systems and by assessing the ethical principles of AI integrated CS in the AQ assessment. according to the literature review, guidelines have been published on how AI should be developed and used, thereby addressing issues serving as a potential threat to both individuals and society. AI products and services ought to be allied with the United Nation’s Sustainable Development Goals (Desa, 2016) and constructively support them,

[6] ATLAS.ti

benefitting humanity. These guidelines are defined as the principles of Trustworthy (Fjeld et al., 2019) as also briefly discussed in chapter 2.

For assessing Trustworthy AI, the significant indicators measuring the performance of AI, concerning its possible utilization in the CS project, have been sourced and have been adapted according to the relevance of this study. Questionnaire for the semi-structured interviews have been formulated using the indicators, the answers to which will be insightful in assessing the possible AI methods for enhancing CS AQ data. The operationalization of AI includes:

Technical Robustness: Refers to the process that ensures safety, transparency, systems reliability, and accuracy.

Social Impact: Refers to the process that ensures inclusive design processes, societal and environmental concern, and accountability for AI systems and their outcomes

To assess the socio-technical factors influencing CS in AQ assessment, indicators have been sourced from the literature review and have been restructured according to the relevance of the study. This includes assessing social and technical factors mediating the relationship between independent and dependent variables. This includes:

Citizens participation and Behaviour: Refers to the participation cycle of a citizen scientist, including and the behaviour change after the participation in the pilot.

Citizens' Perception: Refers to the expectations of the citizens regarding the pilot from the initial participation until the data analysis process of the pilot.

Individual condition: Refers to the specific conditions or factors that personally influence the citizens' engagement in the participation cycle.

Information Systems: Refers to the systems involved in from data acquisition to data transferability. For example, sensors, network, organizational structure etc. This is associated with social factors, as the technical aspects directly or indirectly affect the motivations and citizens' participation cycle.

Finally, the quality of CS AQ data refers to the potential to improve the quality of CS AQ data through AI methods. It is imperative to measure the AI-enhanced data to be able to determine the pre and post AI integration results. ***However, this research aims at proposing the use of potential AI methods for AQ assessment pilots. AI methods have not been used yet for the pilots and the data collected for this study, does not include the results of AI-enhanced data.*** Therefore, to evaluate the quality of CS AQ data, the quality of CS AQ data (the results) and the Hollandse Luchten pilots have been analyzed. However, data quality, especially output data, implying to the AI-enhanced data is an important indicator and should be used in future work. (see section 5.2).

Variables, definitions, indicators framed by the research question, supported by the literature review are presented in Tables 3, 4 and 5 below.

Table 3: Operationalization of the independent variable AI: Indicators, Data collection method, Data Type and Data Sources

Variable	Dimensions	Definitions	Sub-Variable	Indicators	Data collection method	Data Type	Data Source
Artificial Intelligence (Independent Variable)	Process	Possible integration of AI methods or tools in the data analysis process of the Hollandse Luchten pilots.	Data Analysis	Working and quality of sensors	1) Primary qualitative data collection: Semi-structured interviews 2) Secondary qualitative data collection: Online Articles, websites	Qualitative	Primary: Experts from Waag, Province of North Holland KNMI, Sobolt GGD Amsterdam and RIVM
				Data calibration (correction and of data)			
				Optimization of location (where the sensors are placed)			
	Trustworthy AI	The process that ensures, safety and transparency of the AI system. The process also ensures inclusive design processes, societal and environmental concern. (Hleg, 2019).	Technical Robustness	Data accuracy			
				System's reliability			
			Social Impact	Unfair bias avoidance			
				Sustainable AI			

Table 4: Operationalization of mediating variable- Socio-technical Factors: Indicators, Data collection method, Data Type and Data Sources

Variable	Dimensions	Definitions	Sub-Variables	Indicators	Data/collection method	Data Type	Data Source
Socio-Technical Factors (Mediating Variable)	CS (Social factors)	"the science which assists the needs and concerns of citizens and as a form of science developed and enacted by the citizens themselves". (EEA, 2019, p.7)	Citizens' Participation and Behaviour	Motivations for participation	1) Primary qualitative data collection: Semi-structured interviews 2) Secondary qualitative data collection: Online Databases	Qualitative	Primary: Experts from Waag, KNMI, GGD Amsterdam, Province of North Holland, Sobolt and RIVM Citizen Scientists (participants
				Initial and continuous participation			
				Feedback of the citizens			
			Citizens' Perception	Expectations from the project have met			
				Participation in sessions for knowledge building			
				Perception change			
			Individual conditions	Availability of resources (internet access, time and money)			
				Social influence (social relationships, social media)			

				Citizen’s demographics (age, race, and sex)			from CS AQ projects in North Holland) <u>Secondary</u>:	
				Experience in the field				
	AQ Data Information Systems (Technical factors)	Technological factors concerning integration and interoperability with existing systems, for instance, technique usability, network infrastructure and the use of emergent technologies.	Information Systems	Technique usability and tools				
				Network Infrastructure				
				Organization Structure				

Table 5: Operationalization of dependent variable-Quality of CS AQ Data: Indicators, Data collection method, Data Type and Data Sources

Variable	Definitions	Indicators	Data/collection method	Data Type	Data Source
Quality of CS AQ data (Dependent Variable)	The potential to improve the CS AQ data through integrating AI methods	Quality of data (results)	1) Primary qualitative data collection: Semi-structured interviews 2) Secondary qualitative and quantitative data collection: Online Databases	Qualitative	<u>Primary</u>: Experts from Waag, GGD Amsterdam, Province of North Holland, and RIVM <u>Secondary:</u> Articles, Projects website, RIVM and KNMI report
		Accessibility of data			

3.3 Validity and Reliability

The Case Study as a research strategy confirms high internal validity because of the high quality and exhaustive amount of collected information. However, the small number of units (studying a single case) in the study jeopardises the reliability and validity of the case study research (Van Thiel, 2014). Triangulation of data sources, and by using different operationalizations addresses this challenge (Van Thiel, 2014). This means taking a diversified approach (collection of data through primary and secondary sources) more data can be collected which reassures the validity, irrespective of the number of units.

The Case Study research strategy explains a novel or a unique phenomenon in a comprehensive and thorough mode. However, the generalization of the findings to other cases is often challenging because of the uniqueness of the case. This may be stimulating when applied to varied cases, leading to limited external validity (Van Thiel, 2014). The findings of the study might have excluded certain influential factors and without further research, the generalization of findings is considered a restraint in the study. However, the analysis of the secondary data produced through the CS AQ program, combined with the flexibility of the interviews augments the external validity of the research.

To upsurge the reliability of the study, the entire procedure will be conducted in a systematic and standardized manner, which allows for replication or meta-analysis (Van Thiel, 2014). A database and a logbook are maintained for the transcription of imperative data sources and step-by-step operations of the research are maintained to advance reliability.

3.4 Expected Challenges and Limitations

One of the *main challenges* in conducting a case study research is the unfortunate crisis of *Corona pandemic*. Firstly, because of the lockdown scenario, it is thought-provoking to make people agree to be interviewed as face to face interviews might jeopardize the current health situation. For this reason, online interviews were held, however, it is difficult to recreate the energy and spontaneity with online Interviews. Moreover, in-person interviews allow a controlled environment where trust and empathy could be built regarding sensitive information.

Secondly, in the case of qualitative interviews, the perceptions of the citizens might be fluctuating, as it would’ve in normal circumstances. For instance, people might be unwilling to participate and respond with honesty, which will affect the reliability of the results, specifically in the case study.

Thirdly, to formulate more exhaustive research, an ideal strategy would have been to conduct quasi-experiments and evaluating the impact of applying a real AI method integrated into the CS AQ project. The results of which could be compared to the current CS AQ data. This would have included multi measurement observations, with and without the use of AI methods.

Chapter 4: Presentation of data and analysis

4.1 Introduction

This chapter demonstrates the findings which are based on the research question and the objectives. These findings of the research are based on various methods both in data collection and analysis. The preliminary analysis includes descriptive analysis based on the process of the Hollandse Luchten project. Causal relationships will be established on the evidence collected from the primary and secondary data collection methods. This includes the results of the interviews and the findings that are supported through the co-occurrence table and the query tool generated through qualitative data processing software.

4.2 The Case Study: Content Analysis

The content analysis uses secondary data such information about the participatory sessions, newsletters, articles, online data portal and maps. The content analysis is comprised of the detailed structure of the 3 pilot projects, which helped analyse the process or the various stages involved in the project. This helped to reveal and describe the organizational structure and explain the area wise workings of the pilots.

Quotations from the contents on the Hollandse Luchten website by Waag was coded with the same codes used for primary data analysis. For instance, information of the participatory sessions supports the quotations about the information and timeline of the pilot, information on the working of the sensor kits and the network infrastructure through participation sessions, and the information systems, including the working online platform of the pilot. Additionally, frequently asked questions (FAQ) was also analysed from the official website, as it contained significant questions from the citizens (participants) to understand the procedure which helps to understand the perspective of citizens concerning their motivations and technical understanding of the project.

Furthermore, analysing the process and the significant occurrence of events is important for co-dependency of relationships, and also helps to understand the constraints, widening an opportunity for the possible integration of AI

Over 40 documents were viewed, placed in context, and were coded for analysis (Bowen,2003). This included Hollandse Luchten Project related documents, the timeline of participation sessions, newsletters from multiple sources.

4.2.1. Hollandse Luchten Pilots

Hollandse Luchten is considered the citizen platform for measuring the air quality in North Holland. It consists of three pilots named IJmond region (Figure 6), Buiksloterham in Amsterdam (Figure 7) and Kogerveld in Zaanstad (Figure 8). The pilot in the IJmond Region is concentrated around the area of the Tata Steel factory. The Dutch Emission Authority (NEA) in their recent reports, reveals the increase in the emissions between 2014 and 2017. Tata Steel is polluting Netherlands with 6.8 million tons of CO_2 in the air in 2017 (Waag, 2020). The pilot aims to gain detailed insights into air quality around the Tata Steel factory. Waag in the Hollandse Luchten newsletter posted:

> "*On April 19, 2019, Under the watchful eye of more than 100 participants, Hollandse Luchten experienced the official start". (Waag, 2020)*

> "*On Tuesday 11 June 2019, a part of the residents of the IJmond region in Beverwijk gathered to determine for what purpose they want to use the sensors and where they will be mounted.*

This was the first local meeting on the agenda, after which Wijk aan Zee and IJmuiden will also organize similar meetings." *(Waag, 2020)*

Figure 6: Map showing the sensor stations of the IJmond Region. Source: Waag, 2020

The participants, in these sessions, hosted by stakeholders, were asked about the goals and measurement questions utilizing *co-creation methods*[7]. Some of the most important questions were about the influence of various sources like industry, traffic, shipping, from the outside of the boundary; the public places prone to PM, such as schools and sports parks; the places along the bicycle highway, etc. These questions indirectly represent the motivations of the community to participate in the project which will further determine an individuals' will for initial and continuous participation. These participation sessions also signify the importance of inclusiveness which indirectly affects the perception and expectations of the involved community.

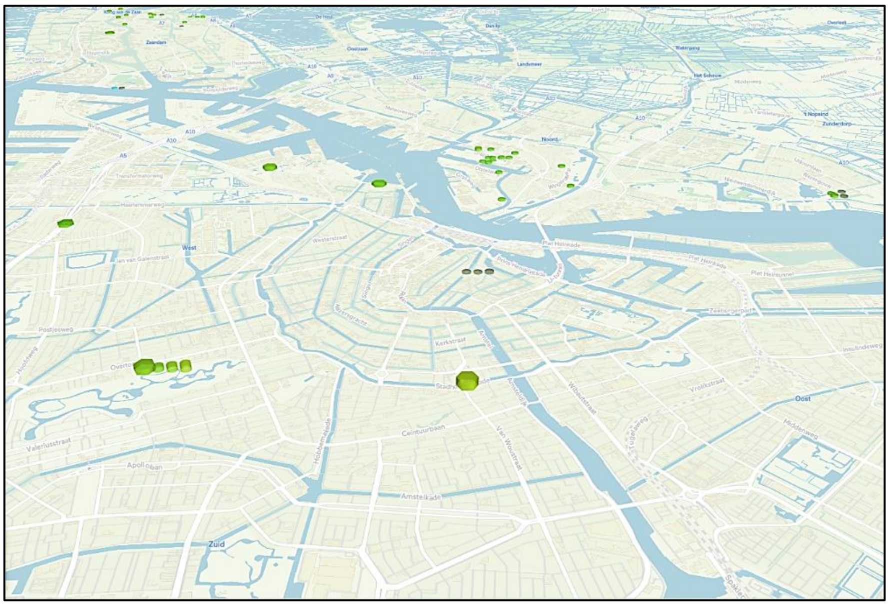


Figure 7: Map showing the sensor stations of Buiksloterham Amsterdam. Source: Waag, 2020

Buiksloterham consists of different new construction projects. This was once one of the most polluted areas in Amsterdam because of heavy industry and shipbuilding. The growth in construction in the coming period is a major concern for the residents. Waag in the Hollandse Luchten newsletter posted:

"*A full house on Tuesday evening 3 September at the kick-off of Hollandse Luchten in Buiksloterham." (Waag, 2020)*

[7] "Co-creation is a values-based, inclusive approach that focuses on bringing together different societal actors around matters of shared concern" (Waag,2020). Refer https://ccn.waag.org/.

> *"Buiksloterham measurement project can contribute to the total knowledge about air quality. And not to forget the total knowledge about measuring and measuring equipment."* (Waag, 2020)

An interesting finding was the diversity of motivations being linked to the specific locations and the air components affecting the particular location. Measuring PM is particularly important in IJmond because of Tata Steel emissions while measuring besides NO_2 concentrations caused by the traffic in North Amsterdam adds another dimension to the data. In the area wise participation sessions, the strategy of measurements and the goals were set by the community, providing them with a sense of responsibility and creating a bottom-up initiative.

Figure 8: Map showing the sensor stations of Zaandam Kogerveld. Source: Waag, 2020

The first meeting of the pilot Kogerveld (Zaanstad) took place on 4th February 2020. The importance of measurements was emphasized and the value of attention for initiating the movement was highlighted. Goals and measurement questions were formulated in groups and it was agreed that some specific spots (A7 & A8 sensors) are the most significant point of focus. The most important questions were about the influence of A8 on the recreation area; the effect of industry on the ambient air quality; the effect of biomass power plant; the effect of traffic on peak levels; the active and passive use of the sports fields, etc.

4.2.2 Sensor Kits and Information Systems

Developed by Waag, the HoLu sensor kit is a modular kit to measure different air components or substances present in the air. The kit is programmed in a way that the user does not need to install any firmware. Figure 9 shows the two versions HoLu kits: Basic, that measures PM, and the Extended, that contains two gas sensors for NO_2 and O_3. An appealing feature about the kit was the do-it-yourself package element, which implies that the user requires to assemble the complete device according to the instructions in the manual provided.

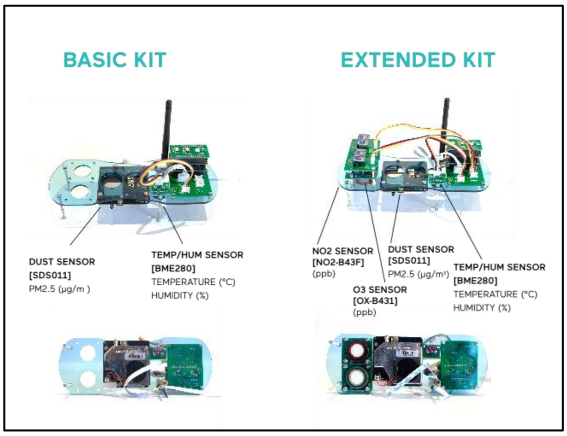


Figure 9: HoLu kits: Basic and Extended. Source: Waag, 2020

The sensor kits in the IJmond region appear on an online map around 18th July 2019, that visualizes data from 200 HoLu sensor kits and the official measuring points[8]. An interesting relationship can be seen here between the sensors and the motivations of the citizens about the curiosity of learning about technology, which also highlights the significance of the socio-technical environment. According to the Hollandse Luchten newsletter:

> "*Research is being conducted into the equality of the data from the HOLU sensor kits, and into the best way in which you can use this data"* (Waag, 2020)

This highlights the importance of the organization structure, as consistent efforts are needed in the complex data analysis process.

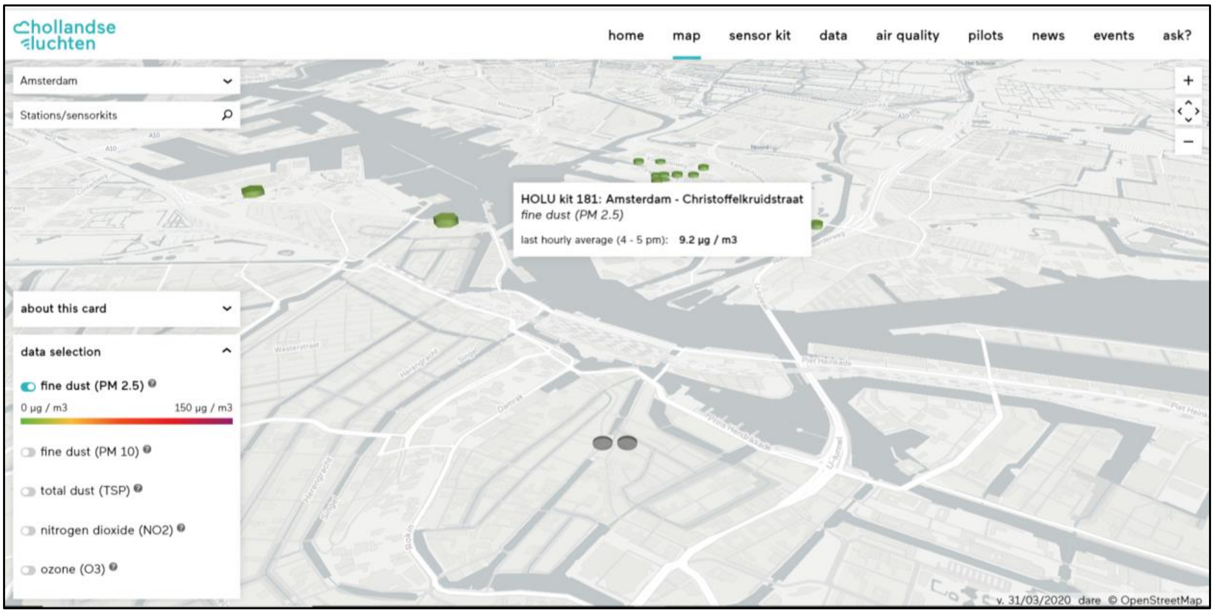


Figure 10: Online map showing data from HOLU sensor kits specifically in Amsterdam and from official measurement points of luchtmeetnet.nl. Source: Waag 2020

Figure 10 shows data from HOLU sensor kits and official measurement points. To evaluate whether the data and the information systems were understandable and reliable, the frequently asked questions (FAQ) has been analysed. It was noticed that a lot of questions from the citizens were based on the data information and the measuring of the various air components. On asking about the reliability of data, Waag answers:

> *"Much research has been done on the measuring equipment used. For example, (…) we know that these official PM_{10} monitors have an accuracy of approximately 11% and for $PM_{2.5}$ 17%. The EU requirement is to be less than 25%."* (Waag, 2020)

The answers also stated that the accuracy of the HOLU sensors is not known, as it can differ from sensor to sensor. Figure 11 shows one of the features of the online map, including the substances that are measured and the hourly values. This data represents the usability and the understanding of the data by a non-expert and implied the user-friendliness of the online platform for easy access of the data to the users. Further, the same information can also be viewed on a phone with the AQ app.

[8]Luchtmeetnet: www.luchtmeetnet.nl provides information about local and offcial measurements, news, air components etc.

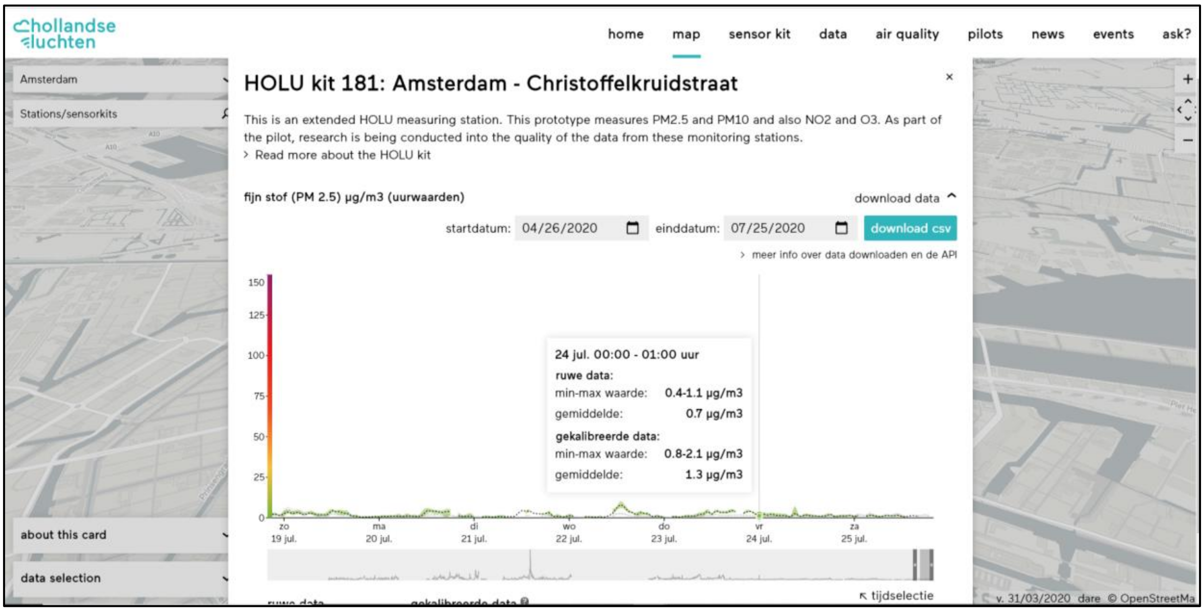


Figure 11: Feature of the online map: Data usability and understanding by a non-expert. Source: Waag 2020

A thought-provoking finding is the importance of stakeholder participation in the whole process of data analysis as a smart combination of reference measurements and calculation models are made at RIVM together with Waag. The reference modelling points at RIVM are significant because they serve as inputs for the models and calibration. These calculation models use the measurements and include the data about the number of cars driving, the emissions from factories etc. The models use data about the weather, such as temperature and wind, which influence air quality.

> "*By using the calculation models, we can not only estimate the air quality across the Netherlands, but we can also estimate what happens when you take a certain policy measure to improve air quality" (Waag, 2020)*

For instance, there are regional background stations that measure background pollution in rural areas, which often comes from far away, for example, London. Additionally, there are also street stations that line busy roads and measure local pollution. There are background stations, which are located in a city but very close to a source so that the pollution spread can measure where many people live. Finally, there are industrial stations that measure in areas where industry and people live. Sometimes, substances like sulphur dioxide are also measured, because of it mainly coming from the industries.

4.2.3 Stakeholders

Hollandse Luchten Is commissioned by the Province of North Holland to research on citizens gaining valuable insights through open source and affordable measuring sensors. Table 6 shows the various partners involved in this project and the description of their involvement.

Table 6: Stakeholders and the description of their involvement in air quality measurement. Source: Author, 2020

Stakeholder	Role	Description of Involvement in air quality measurement and Hollandse Luchten Pilot
RIVM	Partner (Main)	RIVM measures air quality in the Netherlands on behalf of the Ministry of Infrastructure and Water Management, the Province of Noord-Brabant, the Province of Zeeland, the Province of Gelderland, the Municipality of Hilversum and the Municipality of Laren. It mainly calibrates data for Hollandse Luchten pilots.

Waag	Organizer	Waag is responsible for Sensor kits development, Data calibration, Communication, Management for the pilots.
Province of North Holland	Partner (Main)	Responsible for Communication, Management, and data analysis for the pilots
GGD Amsterdam	Partner (Main)	The GGD Amsterdam measures the air quality in North Holland on behalf of the province of North Holland, the Municipality of Amsterdam, the North Sea Canal Area Environment Service, the Municipality of Zaanstad and the Port of Amsterdam.

Other partners include Environmental Service IJmond, Ijmuiden, Buiksloterham Circulair Environmental Service, North Sea Canal, Smart City Haarlem, TATA Steel, Municipality of Zaanstad, Municipality of Haarlem and Brak.

4.3 Data Preparation and Analysis

As described in Section 3., the researcher used qualitative data processing software to conduct data preparation and analysis. The selected 10 codes are presented in Table 7. The coding is done on the indicator level. to have a very clear and precise coding process.

Table 7: Codes and Quotations used in the data processing software. Source: Author

Code Group	Code	Number of Quotations
Artificial Intelligence	Data Analysis	30
	Social	15
	Technical	23
	Citizen Participation and Behaviour	51
Socio-Technical Factors	Citizen’s Perception	62
	Individual conditions	39
	Information Systems	77
Quality of CS AQ data	Data Quality (results)	64
	Accessibility of data	54
Total Quotations		**415**

Table 8: Co-occurrence Table. Source: Author, 2020

Code Manager | Code Co-Occurrence Table

		Accessibility of Data (31)	Data Quality (93)	I: AI: DA: Data callibration (23)	I: AI: DA: Location... (2)	I: AI: DA: Sensors (12)
I: IS: organized structure	46	4	11	1	1	3
I: IS: Interactive Features	15	9	10	1		
I: IS: technical Tools	30	1	5	4		4
I: S: CP&B: Continuous participation	24	1	6			
I: S: CP&B: Motivation	32	1	5	2		
I: S: IC: Experience in the field	12	1	1			
I: S: IC: Resources: Time	8			1		
I: S: IC: Social Influence (social relationships, social media)	18		5	1		
I:S: CS Perception: expectation	21	2	4			
I:S: CS Perception: Participation sessions	26	2	8	2		1
I:S: CS Perception: perception change	27	1	9			1
I:S: IC: CS demographics	6		1			

The interviews were held based on the main objective of the research, which is to reveal AI methods and the factors influencing the relationship between the variables. The results of the analysis are presented in co-occurrence Table 8. The Table shows the causal relations between the indicators or close association of the indicators with others depending on the quotations. For instance, participation sessions are closely related to the data quality indicator (with 8 occurrences), data quality and organizational structure (with 11 occurrences), data calibration and technical tools (with 4 occurrences). These represent a strong association between social and technical factors. The detailed findings will be presented n further sections, classified per variable.

4.4 Possibility of AI integration: Experts' perceptions of CS AQ data: Independent Variable

The possibility of AI integration in CS AQ assessment to answer the sub-question 1, in this research is exploratory. It is imperative to state that the use of AI methods in the pilots is unknown or non-existent and this study specifically aims to explore if the integration of AI in these projects is possible and useful, ***Therefore, AI methods are analysed in this research in two major aspects: i) potential of AI methods in the process of data acquisition to data correction for Hollandse Luchten pilots ii) potential of existing AI regarding the social and technical use of AI in CS AQ assessment projects, which have not yet been implemented for CS AQ assessment.***

4.4.1 AI in Data Analysis of the Pilots

The integration of AI methods in CS AQ assessment can be analysed through data that is realised in various stages of the project. These are i) Working and quality of Sensors ii) Data calibration (correction of data) iii) Optimization of location (where sensors are placed). This corresponds to the expected indicators from theory and the process of the pilots. The research findings in this sub-variable are very critical, and the opinions of the experts are mostly divided. Their opinion also depended on the organisations they were associated with and the specific fields of knowledge they have. The strategy of recruiting AI experts and data scientists from different organisations (Sobolt, Waag, KNMI, Province of North Holland) helped the researcher gain varied insights on specific applications of AI and make comparisons between the current systems and the applications with the integration of AI.

The aspects discussed were about the data calibration of sensors as it is one of the most import aspects in citizen sensing. Since the 200 sensors that were deployed were inexpensive, there was a hesitation to rely on the quality of these sensors. There were shreds of evidence of the complexity of ensuring the quality of sensors. The expert from GGD Amsterdam with expertise as a Data Convener explained the complexity of AQ measurements and explained the difference in numbers concerning humidity and temperature.

> "*There's been a huge number of hours trying to get the data better to improve it (...) there is one organization which is called Waag, which did everything in the field (...). they send it to RIVM, and they treat it in a very difficult way and send it back to this organization to present it on the website." (Ex 3).*

On asking about the integration of AI to improve the quality of sensors, the experts from Sobolt working as the head of AI Toolbox expressed some views:

> "The *combined use of expensive high-quality measurement instrument but a few of them, and then many low-quality measurements throughout the city. And that the combination of those two might strengthen the quality of the cheaper measurement instruments. By studying the relation between the two. So that is one option, but this depends a little bit on the characteristics" (Ex 7).*

Another expert from the Province of North Holland working as a Data Scientist explained the possibility of using AI data mining methods to improve the quality of the sensors.

> *"some sensors individually show strange results. So, we also use artificial intelligence application by using outlier detection algorithm to see which sensors show strange results and then the experts will look at these sensors manually" (Ex 9)*

Respondents had varied views when it came to the application of AI for CS AQ assessment. Five out of eleven experts knew AI applications and methods, out of which only four were currently working directly with the AI methods. The experts currently working in the field of AI responded positively to the integration of AI methods with CS AQ monitoring, however, all four of them also mentioned how research is still being done for such applications.

The second aspect discussed was about the complex process of data calibration. Calibration is one step in the entire process towards validated citizen sensing data. In this case (cheap sensors) corrections have to be applied to account for non-linearities of the sensor response and the drifts due to, for instance, sensor degradation, However, correction is quite challenging as the dependencies of the CS sensor on environmental variables is not well known. As per November 8, 2019, it was decided to remove the sensor for temperature and humidity. After an initial calibration period, it appeared that sensor measurements of temperature and humidity are necessary for correction of NO_2 measurement. During the calibration of sensors, unforeseen challenges were encountered because of the sensitiveness of the sensors. The expert from the Province of North Holland working as an environmental Lead and expert from Waag also explained the complexity of the measurements.

> *"Daily calibrations of the sensor station so serve your measure the sensation and based on data they make an algorithm for calibration every day so we have the raw data, and we have also to calibrate metadata, and publish both so people can see both on our website"* *(Ex 8).*

> *"It's a physical phenomenon, which is not easy to understand and therefore the measurements also reflect are complex (...). The phenomenon is complex itself" (Ex 1)*

The expert from GGD Amsterdam also explained the downsides of the project and explained how the AI can address the problem of shortage of labor.

> "*Downside of such projects is that although you win a lot of money by not spending so much on your official measurements. which are much more expensive, but you lose a lot on your output. Artificial intelligence could maybe help in the future to reduce the number of hours that the experts who still need to put into*." (Ex 3).

The expert from Waag working as a data protection officer explained how the current physical models of calibration are easy to understand but are not the most powerful tools for data calibration. The expert also mentioned of having a society which is going to more adopt to the AI approach. The expert further explained how on one hand there more research is on making ML more understandable, and on the other the reason for society to adapt to this approach because of the upsurge of AI technology in the foreseeable future.

> *"There is this first role of machine learning to come (...), for example, deep neural network or other tools to try to make this calibration more precise (...) machine learning is a tool for a more powerful solution. (Ex 1)*

Furthermore, the expert form RIVM working as an air quality specialist had contradictory views about using ML. The expert explained that ML methods were tested in the process, the results, however, did not reveal the co-dependency of the additional substances that were detected by the sensors. The reason for the influence of one substance on the other remains unknown in using ML applications. The expert said:

> "*We are not so keen on having machine learning, in the sense that you just let all parameters, loose. For example, a lot of parameters are co-dependent. So, if the temperature rises the relative humidity also changes. So, then you do not know anymore, whether it is the relative humidity, or the temperature which does, which has a real influence*." (Ex 6).

However, the expert also addresses the importance of open data and acknowledges the fact that at some point, because the data is abundant, it will be worth looking at ML methods.

The third and the final aspect discussed in this sub-variable is about optimization of the location of the sensors. An interesting finding in this aspect is the significance of placing a monitoring station. The expert from KNMI, working as a Data scientist shares an example:

> "*If you are placing your air quality station next to the parking. You can expect that during weekdays. for example,8 in the morning or 10 in the morning when all the shops open, your station is going to register a higher concentration of pollutants because all the cars are coming in, but it doesn't necessarily have to be representative on the surrounding area"(Ex 2).*

The expert also explains the use of ML in analysing data by saying:

> "*You have these kinds of average function mean function and then you can check for deviations automatically as long as the data can come in. You can use machine learning for anomaly detection. for example. (Ex 2).*

4.4.2 AI in CS AQ Assessment: Technical Robustness

The above section exposed some of the AI methods that could apply to CS AQ monitoring especially at the various stages of the process in the context of Hollandse Luchten pilots. This section will elaborate on the technical robustness of AI, concerning the data and the information systems. It is essential to analyse the principles of Trustworthy AI as explained in the earlier sections applicable to the general setting of AI applications

The main research finding of this sub-variable is the unknown capability of AI. The capabilities of AI are enormous, and the application is universally used. Experts explained that AI can be a powerful tool with extensive technical robustness, however, the contextual setting of the application should be carefully studied for positive results as the threats towards AI is real. During the interviews it was clear that the experts (AI field) had a positive opinion and shared a common vision about the use of AI applications, however, it is important to highlight that all of the interviewees also mentioned about the common threats of AI, and the need for more research and understanding of the context before applying AI methods. The technical robustness of AI can be measured in two aspects i) Data accuracy and ii) Data reliability.

The first aspect examined is about data accuracy. This indicator is derived from the principle of Trustworthy AI (as discussed in section 2.2.1). The expert from Sobolt brought novel insights to the applications of AI methods in the context of resolutions. Resolutions play a significant role in analysing the satellite data, and applications of AI could also be used for the Sentinel Citizen project which is an upscale pilot of the Hollandse Luchten pilot.

> *"Because we are developing a solution to improve the resolution of Earth observation data of satellite data (...). Not many people are doing this but we're very excited about it and it's still at early phases (...) it's possible to increase the resolution." (Ex7)*

The expert explained the use of AI methods to analyse remote sensing data, specifically the satellite data from Sentinel 2.

> *"This is related to this multispectral data Sentinel 2 which gives us multiple measurements throughout the year. We have high-resolution aerial photography from the summer, which is available in the Netherlands for free. And we have a similar source, also for free LIDAR measurements, which is called Actueel Hoogtebestand Nederland (AHN), this is about the spatial structure of, in this case, nature, and we use that to predict the type of nature, for each part of a very large area, and to assist ecologists in their monitoring tasks so they have to make a map of different types of nature within a large area. And we, we help them with that by using these data sources and analysing them with artificial intelligence" (Ex7)*

The expert further explained the method of the application. On asking about which method of AI can be used to increase resolutions, the expert replied:

> "*Machine-learning specifically deep learning. And there is a lot of research out there on what they call super-resolution or single-image super-resolution. Most of the research is not in the domain of satellite data but the domain of photography and social media images, videos, and data compression. So, it doesn't translate one to one to what we are doing, but we use the same concepts and ideas from there to incorporate in our work." (Ex7)*

Further, the expert from the Province of North Holland working as a data scientist also explained how ML methods are currently being used in her field.

> *"We have a student from the University of Amsterdam and he's looking into satellite imagery and he's trying to predict (...)it's an image to text detection algorithm to find all the forest in the\ province so we can calculate the area and see if the forest area decreases or increases." (Ex 9)*

The second and final aspect is about the system's reliability. This indicator is also derived from the principle of Trustworthy AI (as discussed in section 2.2.1. The experts (all four) referred to the application of AI as promising. However, the same experts also raised concerns as the technology is new and very powerful. The reliability depends on a proper validation of results according to an expert. The expert from Sobolt, speaking about the positive applications of AI, mentioned some examples from his work, which implied creating a connection between humans and AI, for also limiting the potential threat that it possesses.

> *"We long for solutions, we try and create a synergy between humans and AI where AI can assist humans (...) Also for making sure that the AI doesn't recommend anything too crazy. the other danger is AI, not being not entirely trustworthy and perhaps having a bias sees a wrong result sometimes. We always look for interaction with humans, for validating the important results. (Ex7)*

One of the experts also explained the complexity of measuring different air components could be less complex by using ML methods, however, the results sometimes may not be trusted, the reason of the influence of factor or another is unknown.

> *"We use machine learning to increase the abstraction and say you have a mix of the factors that contribute to pollution. (...), we need to have a more precise tool (...) results from machine learning might be more precise but people don't trust (...) because we cannot back that knowledge because they lose the cause of connection (Ex1)*

Another expert, working as a data scientist at KNMI, brought valuable insights regarding relying on the future applications of AI. The expert explained how time series analysis can be used for short-term predictions of air pollution through finer monitoring. Giving an example of their work, the expert used ML to monitor 50,000-60,000 observations to prepare a map, to pinpoint the locations in the areas riskier for the people to visit. According to the expert, the same technology could be used in modelling of air pollutants. The expert also specified specific models that can be used for time series analysis. Classical statistical models include Auto-Regressive Integrated Moving Average (ARIMA), or ML models including Gaussian process regression (GPR) which is a nonparametric, Bayesian approach to the regression that is making waves in the area of ML (Ex 10). The expert also suggested using neural networks including Ordinary Differential Equations (ODE) and Stochastic Differential Equations (SDE). Using these might help in short term predictions.

> *"For the bad pollutants, for example, there is something that is more from the weather field, give you some sort of nowcasting (...) like the observations of today one per hour of these pollutants (...)perhaps predict what will happen in the next day, an hour (...) (Ex 2)*

Two out of five AI experts also explained some of the constraints of AI concerning reliability. The expert working as a data scientist at KNMI explained that in principle big set of observations, for instance, in case of millions, would not be a case for using neural networks because of the algorithms tend to be slow when the training sizes are large. In such a case, quality control is necessary, however, it depends on the problem and the situation that is being analyzed. Another expert from Sobolt explained:

> *"AI techniques tend to be statistical in nature. They tend to be probabilistic. So, almost by definition, you will not get 100% correct results (...) This is an abstraction of reality so sometimes the results are a bit off in AI it's much harder to point to why it goes wrong, as its probabilistic model and the origin of mistakes is often unclear. And because it is hard to explain where errors come from it's also a lot harder for people to trust AI, and you need to show every time you use it. It's very hard to validate it. Because of this lack of expandability. I think that's one of the bigger constraints we have." (Ex 7)*

> *"there are infrastructural issues about meaning a lot of storage space and computation power (...). It just requires some more investment, not something that stops us from using it." (Ex7)*

4.4.3 AI in CS AQ Assessment: Social Impact

According to the literature, and the principles of Trustworthy AI, evaluating the social impact of the application of AI methods is essential for an inclusive society. Social impact can be measured in two aspects i) Considering unfair bias avoidance ii) Ensuring the social impacts of the AI system are well understood.

The first aspect discussed is about unfair bias avoidance for the use of AI applications. Data sets used by AI systems for both training and operation may include inadvertent bias that could lead to unintended prejudice and discrimination. This indicator is derived from the ethical principles of Trustworthy AI (as discussed in section 2.2.1) which is an essential indicator to be analyzed regarding AI application specifically in the case of CS. The expert from Sobolt shared intriguing views about following the ethical guidelines while applying AI methods. The expert explained that the ethical guidelines apply to different sectors of its application.

> *"They're a lot stricter when you use personal data when you make decisions that might be biased towards certain subgroups of the culture, or these kinds of things so it's a lot easier to use." (Ex7)*

The AI experts from Sobolt and Waag also had some concerning revelations on AI being trustworthy, concerning the unfair bias avoidance, however, the expert implied that human interaction with the system for validating results is required for relying on these results.

> *"So, the threat is real as we know (...) so many cases in which we're challenging artificial intelligence, because of the bias because of the fairness" (Ex 1)*

The second aspect analysed is about sustainable AI. This can be interpreted by looking at whether AI is sustainable, and if AI is used for the benefits of society. All five AI experts showed a sense of positivity towards using AI applications in future based on the different sectors of fields and organizations they are associated with.

> *"We're a very purpose-driven company. So, we like to focus on how we are benefiting society or people. And from that message, you can explain what the AI is accomplishing and what it's trying to do." (Ex7)*

> *"We are going to have a society which is more and more adopting this approach. So, on the one hand, we have a lot of research that is trying to make machine learning more understandable. And on the other hand, rather people use more technology. (...) increase over capability to understand how to accept and increase it because this technology will be used in the foreseeable future (Ex 1)*

4.5 Socio-Technical Factors: CS (Social Factors) and AQ Data (Technical Factors): Mediating Variable

For the possible integration of AI to improve the quality of CS AQ data, it is imperative to analyse the variable mediating the relationship. Both the social and technical factors hold a substantial amount of significance in improving the CS AQ data. For this reason, pieces of evidence from both primary and secondary data will be revealed in support of the arguments. ***For secondary data analysis, a survey that was conducted by Waag, in collaboration with the Province of North Holland, has been analysed by using the same coding scheme used for the rest of the data.***

4.5.1 Citizen Participation and Behaviour

The data analysis of the sub-variable 'citizen participation and behaviour' can be measured by i) Motivations of the participants, ii) Initial continuous participation and iii) Feedback from the participants. The survey by De Waag was conducted in Dutch, the answers to which were translated into English and are presented in Chart 1. The questionnaire was distributed in April 2020 via email. All 107 participants were approached, of which 60 participants completed the questionnaire (56%).

The first aspect that discoursed is the motivations of the participants. The motivation of the participants to participate voluntarily in the project provides valuable insights into the intrinsic motivations, which translates into their goals they aim to achieve with the project and the expectations they have from the project.

The results of the survey correspond to the results from the interviews, and the perspectives of both the experts and the participants align concerning the different motivations stated in Chart 1. Motivations ranged from awareness about air quality and different environmental issues to curiosity about technology. These results correspond to the research findings of the interviews. Both experts and community leaders agreed on the different range of motivations.

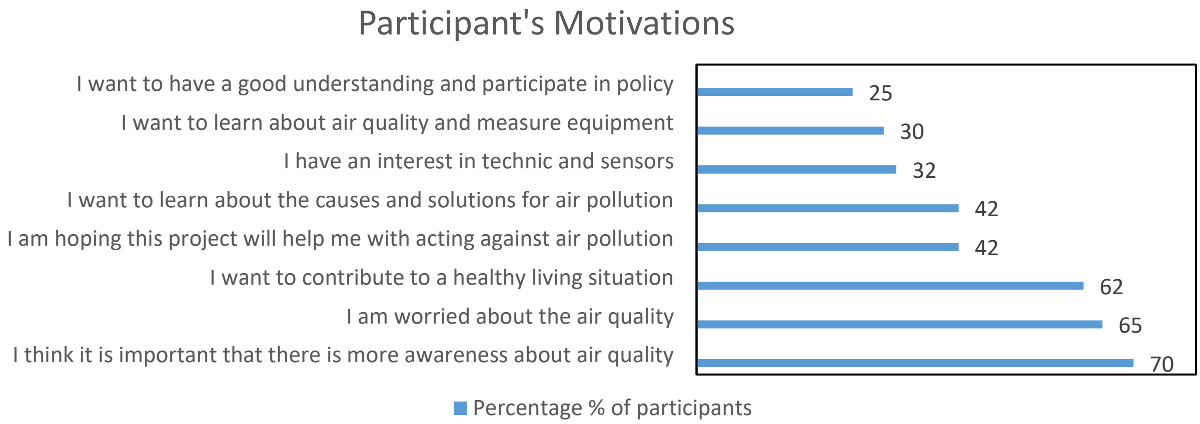


Chart 1: Participant's motivations. Source: Chart by author, data by De Waag.

> *"We want a more detailed view (...) because you want to have a dialogue, at the beginning of the policymaking. That involves all parties where the government is involved where a health institution offers where citizens are involved." (Ex 8)*

> *"So, we gave the spare parts and they had to assemble it themselves, which got them into the technology and know-how it works and knows what kind of parts are in a sensor and what happens with data." (Ex4)*

An interesting and important finding is that motivations were also linked to the specific area and the activities happening in that area. For instance, according to both the experts and the participants, emissions from Tata Steel were of major concern for the citizens in the IJmond region.

> *"getting the data and going to Tata Steel and tell them to shut down your factory" (CS 2)*

> *"Tata Steel is considerably the largest shareholder in the degree of air pollution. (...) . For most participants from the region, participation is mainly aimed at making a stand against this" (Ex 5)*

> *"I saw very clearly happening in this last meeting with the people who community meetings, we sort of always assume that people want to do measurements, want to have a measurement system in their backyard, because they want to know their place" (Ex 6)*

The second aspect discussed in the sub-variable is about the Initial and continuous participation, that is, the participation cycle of the volunteers. This can be interpreted as the necessary steps or ways by which the initial and the continuous participation is ensured by the organizations and the conditions that these factors depend on. From the responses, it was clear the reasons for initial and continued participation were directly associated with the motivations and expectations of the participants. The expert from Waag, working as a communication head explained that the goals of the measurements were formulated by the citizens in the structured sessions and that differed from region to region. Both experts and community participants had a positive response with the continued participation of the citizens. Data from the survey revealed that 92% of the respondents wanted to proceed in the pilots.

> *"So, we organized a lot of local meetings, in the beginning, to explain what we were about to do and to explain our approach, which is a bit different than normal citizen science projects." (Ex 4)*

An interesting finding is how continuous participation was also dependent on the participation sessions and the overall communication and network infrastructure, establishing the importance of the socio-technical environment.

> *"I built already my gateway. So, if you're also a gateway to a show I can easily test if we infrastructure is not working. So that is for me, a thing" (CS 2)*

> *"These measuring stations, can break down and need to be repaired" (CS 1)*

> *"We don't like the pollution here so we're going to participate but then (...), maybe that the network doesn't work (...), some people lose their interest. (CS2)*

The third aspect discussed is about the feedback of the citizens in the process of the project. The expert from Waag, working as an intern for the impact analysis of the pilots, conducted the survey and was also interviewed. The expert explained that the participants did not have satisfactory opinions concerning the feedback of the participants. Also, participants commented on the requirement for an exclusive platform where participants from different regions could interact with each other. Another expert from the Province of North Holland enlightened that most of the participants required more support on the technical and financial front for more growth and involvement.

> *"there was not enough communication amongst them. So, they had this Facebook group, but it's been also a process because that is not a big fan of Facebook." (Ex5)*

4.5.2 Citizens' Perception

Sub-variable Citizens' perception is another important element that is analysed in this study. Citizens perception can be measured as i) expectations from the project ii) participation in sessions for knowledge building iii) change in perception after participation.

According to the survey conducted by De Waag, almost all participants (92%) indicate that they want to remain involved in the project. The reasons were given by the 5 participants who dropped out: "I don't feel that continuation will lead to more results or deeper insights", "poor communication" and "I will continue to check the site, but I don't have to do anything with it."

The first aspect was about the expectations of the participants been met by the project. A stimulating finding is important for managing the expectations of the participants. The experts of the organizations mentioned how the data interpretation is related to the expectations of the people and how significant it is to manage these expectations through clear communication, as it may affect the continuous participation of the participant. Moreover, according to the survey analysis report by De Waag, the expectation about the data may also be related to the amount of knowledge and experiences that the participants have with measuring the air quality.

> *"some people who felt that the day that they were going to get, was going to be very impactful from the start (…)*but they expected there to be a lot of analysis also *done or to be like there to be more of an overview of how did the data changed (Ex 5)*

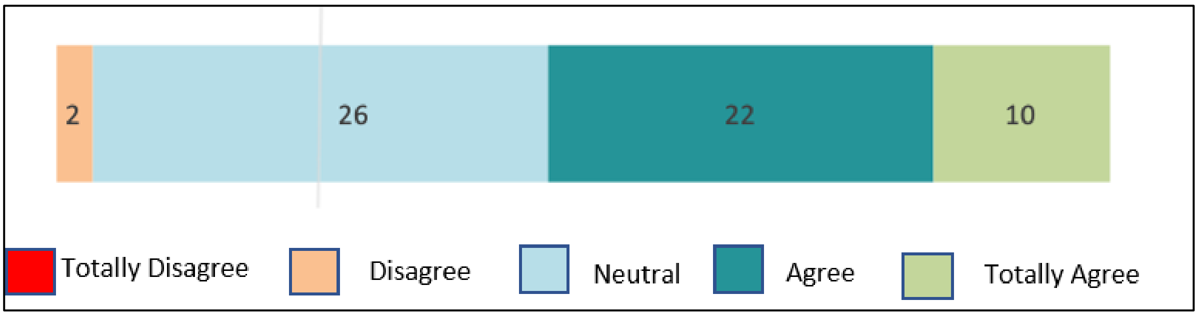
> *"if you have a lot of data that says something about the air quality, which is bad, and then afterwards nothing happens, it's a big risk that people also tend to quit or early of the project then because they might get a bit cynical or, you know, frustrated or angry that nothing happens while we're not the one that's going to change the policy" (Ex 4)*

The second aspect discussed was the significance of knowledge sharing in citizen science. Participants perception also relied on how they valued the knowledge building in the participation sessions. Chart 2 represents the results from the survey, for the question: 'Hollandse Luchten has helped to increase my knowledge about air quality'.

The Chart shows that 26 out of 60 respondents were neutral about the increase in their knowledge about air quality and 22 out of 60 respondents agreed to the same.

Chart 2: Building Knowledge. Source: Waag,2020

Both the experts and the citizens explained the significance of participation sessions as the



foundation of knowledge sharing, and since these sessions are the source for all the communication between, the citizens and the organizations, experts and citizens also suggested the need for improvement in the organization of these participation sessions.

> *"So, we are going to make sure that it is easier to exchange information between the communities (…), how can we talk with others who are doing the same. We are trying to improve in the next phase of the project." (Ex 8)*

> *"We decide the measurement strategy, but also exchanged (…) with houses with pollution and there's a lot of building activity in the effect of that" (CS 1)*

The third and the final aspect discussed in the sub variable was about the change in their perception after being involved in the project. According to the survey conducted by De Waag, one question was about the change in behavior/perception through participation. The results are shown in Chart 3. 57% of the participants responded for ‘I try to bring the problem to the attention of the people I talk to’. More insight into the living environment is expected to contribute to more conscious and greener behavior. The nature of the problem may play a role in this assumption. In the IJmond region, Tata Steel is considerably the largest shareholder in the degree of air pollution. It is understandable that in addition to this ejector it feels useless to adjust individual behavior. For most participants from the region, participation is mainly aimed at making a stand against this. Otherwise, for example, it is in the Buiksloterham district; a pioneer in sustainability; here there may be more attention for which behavior residents themselves can adapt and what effects this has on the living environment. Contrary to expectations, however, the participants of Buiksloterham show little to no changes in their behavior.

These results also correspond to the findings from the interviews.

> *“And some people that got a little bit more conscious and aware of their lifestyle so maybe considered buying an electric car or using public transport more often’ (Ex 5)*

> *“local issues and people observing like woods, smoke from wood fires coming from the chimneys and that they want to know like what's the effect of that.” (CS 1)*

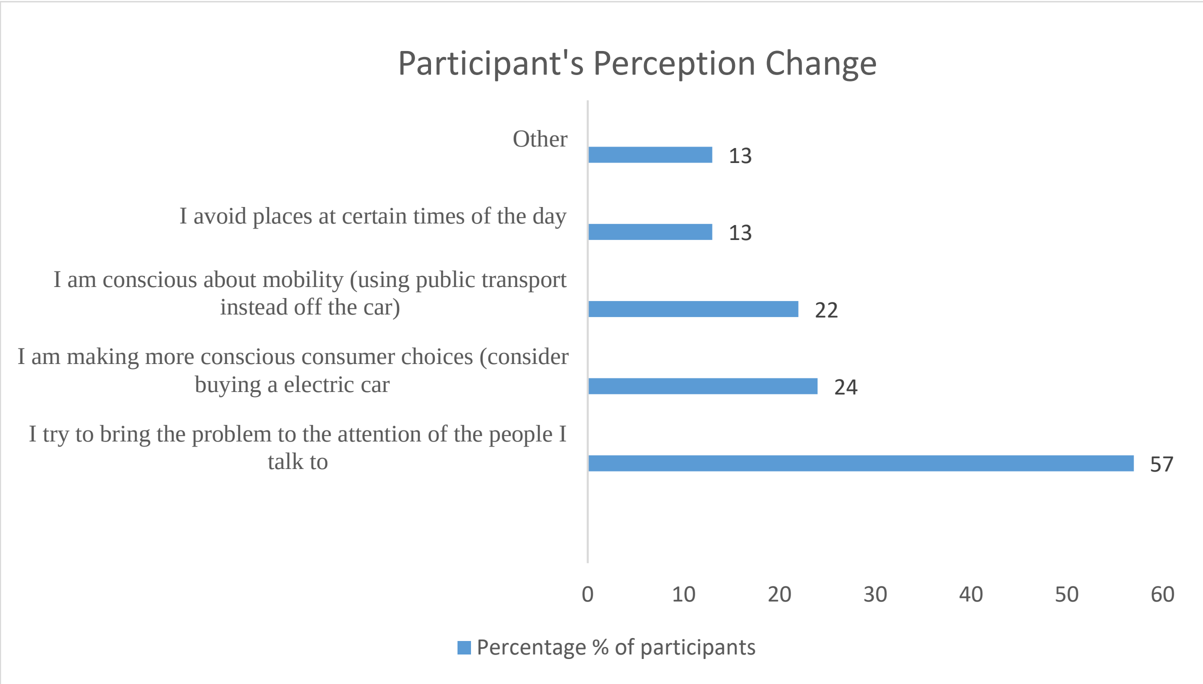


Chart 3: Participant’s perception change. Source: Chart by author, data by De Waag.

4.5.3 Individual Conditions

Sub-variable individual conditions can be measured as i) Availability of resources (internet access, time and money) ii) Social influence (social relationships, social media) iii) Citizen’s demographics (age, race, and sex) iv) Considering experience in the field.

The first aspect of deliberated was the availability of resources. Both the experts and citizens agreed on the fact that time is the most essential resource as a participant and people with full-time jobs or who are studying might not have time to visit meetings or to consistent analysis data through their sensors. Both the community leaders dedicate on average, half a day (four to five hours a day) in a week for the pilots. Apart from time, a computer with an internet connection is also a significant resource for measuring. This might also affect the participation of various individuals.

"I have a few people who even don't have a computer, Older people, but they're still interested because then I print weekly things out and give it to them. And they're also enthusiastic so if you don't have internet. Yeah, then then you must find other ways, but bottom line you need internet connection" (CS 2)

"I think four to six hours a week. And sometimes it's in with us excluding meetings, day to day business, talking to people putting sensors up" (CS 2)

According to the research findings of the survey by Waag, 42% of the respondents view the data weekly, 25% monthly, 18% daily and 15% hardly or never view the data. (see Chart 4). This also relates to the citizens' demographics, motivations, expectations and perceptions.

"People asked a lot of time from participants and people who have full-time jobs or studying might not have that time to have to visit meetings to check on their sensor (...) participants in involvement in time and effort and intention. So, I think people who are a bit older tend to have a bit more time." (Ex 4)

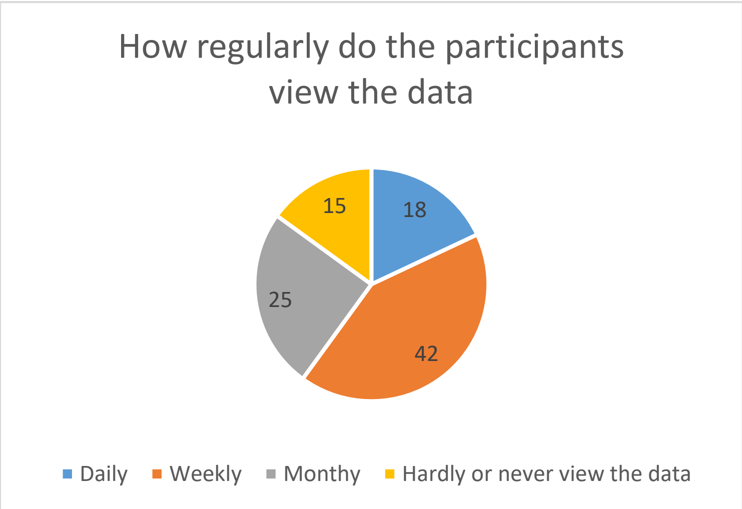


Chart 4: Data Viewing by participants. Source: Chart by author, data by Waag 2020

The second aspect conversed was the social influence. Before and during the start of the project, there was a lot of attention from both local and national media. There were extensive articles published supporting the project and the communities involved in the project. This attention according to the experts and the citizens helped put enormous pressure on policymakers.

"There are also a lot of people who are, let's say organizing them in little groups like in Wijk aan zee" (CS 2)

Yeah, there's a website (...), called start slop for this area where stories are well attended still must develop and we must come from more (CS 1)

"So far, I haven't seen a lot of articles in newspapers (...), it could be more, it could be more community building" (CS 2)

"There's be extensive coverage on both television and newspaper localization" (Ex 6)

The third aspect reflected in the citizens' demographics. Of the respondents, 63% were over 55 years old, 31% between 35 and 54 years old and only 5% between 18 and 34 years old. It is noteworthy but not unknown that the target group's age is so high. Because of this distribution, it was decided not to make comparisons between the variables per age group. However, these results highlight the selective target group of the project and serve as an invitation to investigate how a younger and more diverse target group can be reached in the future.

"But I think the biggest part was older men about 50 plus, who think we live there for a long time we're very involved in neighborhood groups and committees (Ex4)"

"Both he and I have retired from work, so we have plenty of time on our hands. And so that is a sort of muddling up an issue here. I mean if she had a full-time job or a family or a business to run. Then, you simply don't have the time to invest in learning" (CS 1)

The fourth aspect is experienced in the field. The expectations about the data may be related to the amount of knowledge and experiences that the participants have with measuring air quality. ***The more knowledge about measuring air quality with low-cost sensors, the less high the expectations of the possible impact of the data.***

"And the reason for that was I wanted to know about the environment, but also to build it, because it's was a technical piece, and I have a technical background" (CS 2)

"I had already had this knowledge. I'm also in terms of the research methodology, I had technology" (CS 1)

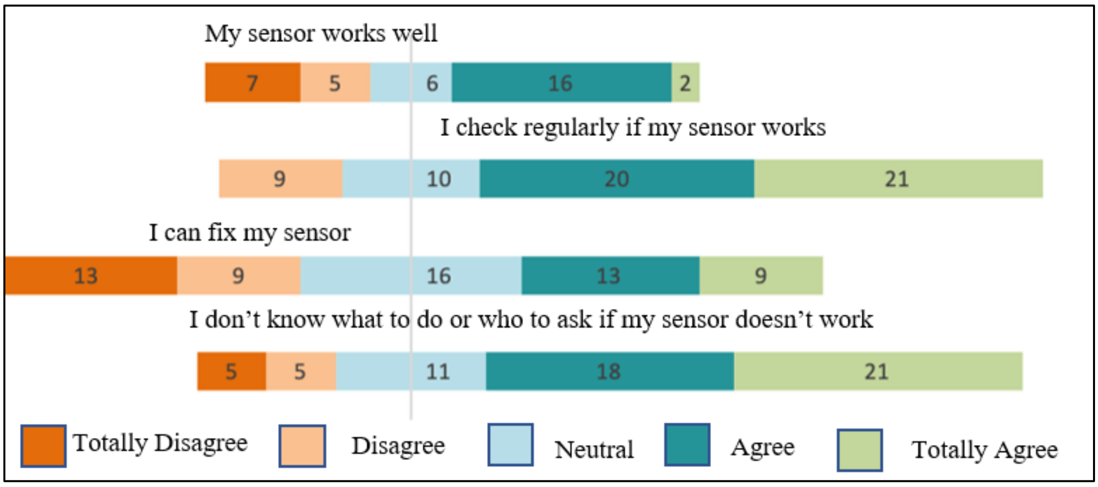
"when you look at the like demographics of the participants. It's mainly old white guys 55 plus, that have probably a lot of time, besides their job or even stop working. It's a specific target audience. One of the challenges also for the project is to see how they can evolve and more diverse population" (Ex 5)

4.5.4 Information systems

The sub variable information systems can be measured as i) Technique usability and tools, ii) Network infrastructure iii) Organisation structure.

The first aspect discussed is about technique usability and tools. According to the survey, the experience with the technique was also questioned (Chart 5). The participation sessions played the most important role in data interpretation sessions, as the respondents without any knowledge could not understand the complexity of the installations and the working of the online platforms. Moreover, experts and citizens mentioned about the interactive features developed by the organizations that allow citizens to, for instance, compare sensors with other

Chart 5: Evaluating technique usability and tools. **Source: Waag, 2020**



sensors, and with the official measurements over time. The expert from Waag explained how respondents had divided opinions about the usability of the data, which is challenging, as it increases the complexity of combining different perspectives in the project.

The second aspect discussed is about network infrastructure. This is an important indicator as it directly affected citizens perceptions about participation. Both experts and the community leaders felt that there was sometimes, communication issues regarding understanding and explanation of data to the citizens without any prior experience in the field of monitoring or data analysis. This would result in the decelerating of the process.

> *"And maybe this is also the difference between a scientific person and a civil person. And that person should be in between like a communication person or an expert" (Ex 3)*

> *"With so many people involved from RIVM, also to communicate between the different project groups, was a problem. RIVM must keep track of the people who were working on the sensor system, and the people working on the data science, people working like me on the communication to keep everything alive. That was really, that was a problem." (Ex 6)*

Both the experts and the community leaders explained various network failures faced by them at different phases and process of the pilot. These ranged from sensors, networks to calibrations. There is also a strong association between network failures and the integration of AI to minimize these technical constraints as mentioned in the previous sections (Section 4.4).

> *"the data connection. Getting the data from the sensor to a central point. That was because they had a LoRA network, that was a challenge. And that is a very stupid problem, which is data connectivity" (Ex 6).*

> *"if you look at the data, there are quite a few sensors that are either completely off or that they have signals that are not the truth, a few thousands of microgram rounds." (Ex 3)*

The third and final aspect discussed was about the importance of organizational structure. The importance of organized stakeholder participation is realized in evaluating the process of the project shown in Figure 12. According to the experts, there has been a huge number of hours to improve the collected data. The collected data is then sent to RIVM, for calibration. Simultaneously, Waag assists the citizens to install the sensors. Waag is also responsible for correcting the data, maintaining the network infrastructure, managing the data infrastructure and visualization od data. Apart from the technical aspect, GGD, Province of North Holland, RIVM and Waag are also responsible for the social aspect in the process, for instance, communication, knowledge sharing, meetup sessions, etc. (as discussed in section 4.2.4).

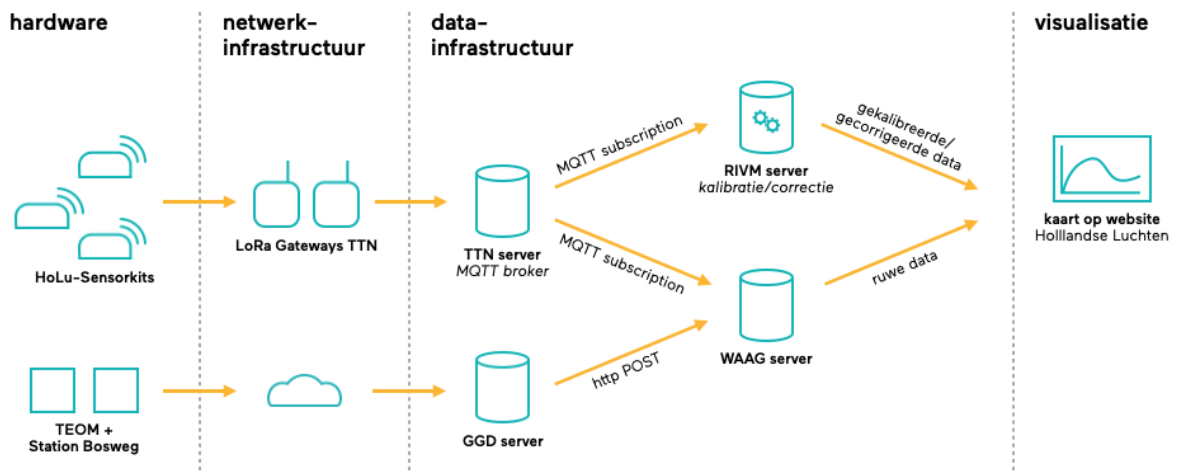


Figure 12: The technical process of Hollandse Luchten pilot. Source: Waag, 2020

To support the above secondary data both experts and community leaders (Ex 8, Ex 4, CS 1, CS 2) were questioned about the importance of organized stakeholder participation. Without the participation of social-technical driven organizations like Waag and RIVM, the project would not have been possible. Although Hollandse Luchten is a bottom-up, citizen-led initiative, the contribution of stakeholders is noteworthy and substantial concerning the operations and the implementation of the pilots.

"You start with a small group, but it grows and then you have to get all the people who are full here to get some stake in the project (...).you have GGD like RIVM, there are a few core players who are in it. And, and now has to make a much broader organization." (Ex 8)

An interesting finding was both the community leaders mentioned that the process should be more bottom-up, implying more community involvement concerning the core decisions of the projects.

"And where we can actually as local communities, sit at a table with the province of North Holland and next to RIVM where we are discussing what should be improved, you're missing this type of analysis, in terms of where the money goes which software developments, which additional data collection" (CS 2)

"It has to be improved, in the area of governance, in the area of communication. The project was very much organized in a top-down, and it should be more bottom-up. (CS 1)

Another interesting finding including in maintaining a concrete organizational structure was the recruitment of the Hollandse Held, i.e. Dutch Heroes. These were Community leaders with some technical expertise, that acted as a middleman between the rest of the community and the stakeholders.

"ask some people from certain areas to be the foreman, Dutch. Hollandse heroes. So that they can explain to other civilians, what is happening, t it's explainable" (Ex 3)

The expert from the Province of NH explained the importance of organizational structure also in decision making. For instance, the decision about displaying faulty measurements can sometimes affect the perceptions about 'hiding' the data or not being completely transparent with the participants. This can affect the continued participation of the citizens. However, showing the faulty measurements also require a detailed explanation and understanding from the participant's point of view, hence creating complexity in the decision-making process.

"The project is upscaling into more communities but there's also going to have a big project organization because there are so many questions. Our group is now simply too small to organize all this, so we have to invest more in support because some people are very socially efficient that can organize themselves but you also have people in the community who simply need more support to get everything going so."(Ex1)

"I had to beg for spare parts. And now I have spare parts but sometimes it takes too long." (CS 2)

4.6 Quality of CS AQ data: Dependent Variable

Quality of CS AQ data refers to the potential to improve CS AQ data through AI methods. Variable data quality can be measured in two aspects i) quality of data (results) and AQ devices ii) accessibility of data. This sub variable associates to the technical robustness of AI, as determining the quality, accessibility, and usability of data, elucidates the potentials of AI integration to the process.

The first aspect is about the quality of data (the results) of Hollandse Luchten pilots. A stimulating finding of this indicator is the association between different air components. The research findings suggest that the quality of the data depends on the various air pollutants as the working of the sensors varies with the different components, for instance, an expert from Province of NH explained how the quality of $PM_{2.5}$ data is fairly good and reliable than PM_{10} and NO_2 measurements. This is mainly because of the chemical nature of NO_2, that makes it more complex to measure., which also affects the making and functioning of the sensors. Apart from this, experts and community leaders had a diverse opinion about the quality of the data and the information systems.

> *"a lot of people who are using this (...) the interface on the website is already good enough to see the data" (CS 2)*

> *I'm satisfied with the devices. It has a good design choice of components is an option to an extent (...) the platform, which you know is this visualization method is done, it's been done quite well. So that for a public it's very easy to see how much polluted or not the areas (CS 1)*

> *"The first step was that they were quite happy the quality of the data, although the sensors are cheap. So, they were amazed by this how producible the measurements were so that a couple of locations there's more than one sensor" (Ex 9)*

RIVM determines the calibration function for each sensor and then applies it to the field data. Once the calibration is completed, the field data is corrected by the RIVM applying the calibration function to the field data. However, the RIVM also wants to develop correction methods to try to compensate drift of the sensor (due to sensor instability issues), RIVM does not calibrate the ongoing measurements. They apply the calibration function and maybe a correction function to create "corrected" field data. However, these "corrected" data can still deviate considerably from reality, if (for example) the sensor is not stable.

> *"Raw data is being calibrated by RIVM and they upload it again to the website. So, the moment we download things. We will get a calibrated set and the raw data set" (Ex 9)*

The second aspect discussed is the accessibility of data. This can be interpreted as the process of accessing the data, which is already available on the data server for analysis purpose by the citizens, and the experts from different organizations to investigate and calibrate the data. According to the survey, the extent to which the data has been made accessible has been tested based on the questions "I think the data is usable" and "I can independently analyse the data" (Chart 6). Although implicit, these figures indicate that the data is of a certainly added value for many participants. In general, these participants are also participants who are good at handling the data. But this does not apply to everyone. There is also a group of about 10 respondents who, although they indicate that they do not find the data usable or can analyse it, look at it every week. Corresponding these results to the findings of the interviews, both the experts and community leaders responded positively concerning the ease of accessing the data from the online systems.

> *"It's very well arranged with open calls so that's, for example, I can do my analysis or check for a machine station how it is doing. For the moment, open data and the extra accessibility testing fairly well thought" (CS 1)*

> *"Most immediate benefits are that you get more data for per unit area, and you get more data per unit of time" (Ex 2)*

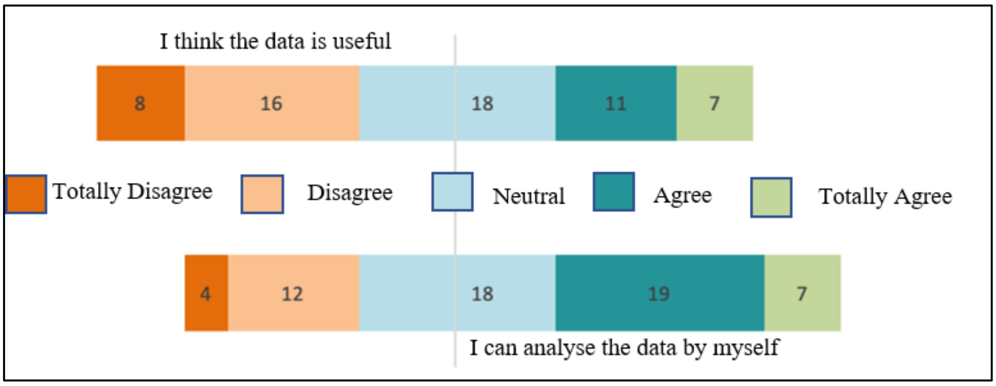


Chart 6: Data Interpretation. Source: Data by Waag, Chart by Author.

Furthermore, experts and respondents also mentioned that as they started involving themselves in data analysis, the complexity in interpreting the data was realized, especially for the users without any experience in the field.

> *"We gave them opportunity to look at the data and to use the data, but we found that the analysis of the data interpretation of the data is very difficult". (Ex 6)*

4.7 Discussion: AI integration for CS AQ data; Practical Implications

According to the theory, AI methods can be integrated with the different aspects in the process of CS AQ monitoring, namely, data analysis (especially calibrations), optimization of location and increasing resolutions (using satellite imageries). Simultaneously AI methods should also serve the purpose of integrating various resources to answer the questions of the citizens. The evolving means in AI and ML can deliver support to CS AQ data for "automated processing and analysis and increase the reliability through data quality assessment" (Can, 2020, p.27). Because of the involvement of the citizens, it is also imperative to analyse the potential threat of AI applications that can serve as a threat to the society or the environments, The data analysis on the integration of AI with CS AQ projects has shown a positive response amongst the experts (especially working in the field). Some experts explained the possible AI methods that can be incorporated into the process of CS AQ monitoring, which includes machine learning, deep learning and neural networks for different data analysis tasks. However, the experts also explained the threats that AI possesses. Therefore, it is essential to apply AI methods with human interactions to minimise these threats at most.

Subsequently, the socio-technical factors play a vital role in mediating the relationship between the independent and dependent variables. All concepts were measured by mixed methods (primary and secondary sources and data) which facilitated in the development of the theory, based on which valuable relations were established. For instance, Individual Conditions and citizen participation are directly related. Based on the indicators, citizens' behaviour and motivations are influenced by the participants' experience in the field and vice versa. It is also noteworthy that the more time (resources) a participant has, the longer the participation cycle is of a participant.

It is imperative to mention Sentinel Citizen pilot, an upscale of Hollandse Luchten that included Earth observations combined with citizen sensing. Combining CS and AI can generate a plethora of knowledge by the citizen scientists that can assist or validate AI algorithms. This serves as an additional data source to process or support semantic annotations of Earth Observations imagery (Schade, S. et al. 2020). AI can also support in filling gaps in data and detecting outliers to enhance the quality of the data, especially from unknown resources. This will require AI data mining techniques, typically used for big data issues. Although the arising opportunities are diverse, it should be highlighted that this vision comes with challenges. Trustworthy AI (Hleg 2019), guidelines should be emphasized as people might not keen to be directed or controlled by AI algorithms. Citizen scientists might not trust the vision that the data produced by them is handled or imperative decisions are made by systems that are machines or black boxes. Overall, both the shortcomings and virtues need to be addressed in combining CS and AI. The benefits of a wise and planned approach to AI including the ethical guidelines are diverse. This ranges from increasing user engagement in scientific actions to fabricating improved scientific conclusions. It is also significant to make informed decisions, examining the risks and opportunities of AI, for instance, the citizens need to acknowledge for producing the data that used to train the computer-vision algorithms to avert the concentration of wealth and power in the hands of AI companies, simply implying, the regulation of data ownership requires attention.

Overcoming the challenges and improving the CS AQ data of Hollandse Luchten pilots, particularly data quality and management, offers a remarkable opportunity to take advantage of evolving technologies like AI, fill data gaps and meet commitments to improving digital illiteracy. To fulfil this potential, CS will require to improve the experience of participants considering their motivations indirectly affecting their perception. Now that CS has been recognised for its social and scientific benefits, investments should be made to increase our ability to appropriately understand stakeholder needs and inconsistencies in data collection by integrated valuable AI tools to harvest the influx of information with utmost accuracy.

More generally, these basic findings are consistent with research showing that the integration of AI and CS, especially for AQ assessment presents substantial long-term capacity. Initial results from some recent projects suggest that AI is already starting to achieve this potential. “Data capturing requirements can help to shape CS actions in a way that would benefit the optional combination of human intelligence and computational power” (Schade, S. et al. 2020).

To conclude, experts fairly believed that one of the powerful elements that AI possess is its ability to conclude a large amount of very complex data, for instance, combining different data sources from one type of measurement from a specific period with a different city with more recent results. Conclusions from both the sets through different time series and perhaps, 100 different experiments, is a type of task that AI can contribute to (Ex 7). However, experts also explained that the complexity of the models lead to complex section analysis and since AI is new, deeper research is needed to benefit from the prominent advantages of AI methods.

Chapter 5: Conclusions

5.1 Introduction and Conclusions

This research explored the potential of AI in enhancing CS for AQ monitoring. It focussed on the relationship between AI and the improvement of CS AQ data. This relationship is mediated by socio-technical factors. For this purpose, Hollandse Luchten pilots in North Holland, a single case study was analysed to accumulate in-depth insights from experts and the citizens to draw more comprehensive conclusions with higher validity. To evaluate the assumptions of integration of AI for improving the CS AQ data, the potential of AI methods was measured concerning the social impacts and the technical robustness of AI. This was derived from the theory (see chapter 2). Moreover, because of the direct involvement of the community into scientific research, that is, CS, the socio-technical factors became a significant aspect of this study as a mediating variable in the research. This is also evident in the research findings presented in figure 13. The figure represents the cycle of socio-technical factors affecting citizens' participation cycle. The conclusions are derived from the research findings presented in Chapter 4. The participation of citizens depends on their perception or behavioural change, which are directly affected by their motivations. These motivations are influenced by the quality of data, which determines whether the citizens can rely on the data or not. This eventually directly creates the expected impact of the pilots on the citizens' and society. This also corresponds to the theory presented in the literature review section in Chapter 2. Therefore, to achieve improved (AI-enhanced) CS AQ data, socio-technical factors play a substantial role.

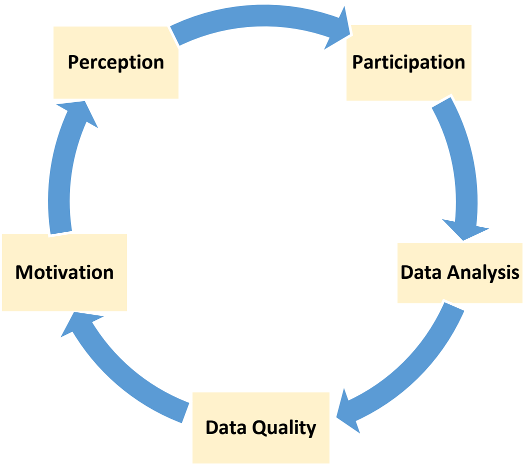


Figure 13: Socio-technical factors affecting citizens' participation cycle in Hollandse Luchten Pilots. Source: Author, 2020

5.2 Answering the Research Questions

Sub Question 1: Which AI methods are advantageous/beneficial for improving CS AQ data and information systems?

AI methods can be integrated into the process of data analysis stages ranging from calibration methods to increasing the satellite image resolution and can be applied as per the expert's recommendations. An important factor and a challenge are the data quality of data produced by CS. Sensor technology has a major impact on air quality issues. Cheaper sensors are getting better and better and can be used so that citizens can now collect data about their environment. However, the quality of these sensors is problematic, especially while analysing the data, particularly, while selecting the data sets and calibrations. To reach an acceptable level of measurement accuracy (to remove sensor artefacts as much as possible) calibration measurements (co-located in-situ comparisons between a reference instrument and the HoLu sensor) have to be complemented with simultaneous, co-located observations of the environmental conditions. Based on the calibration data and the environmental variables, and by applying either analytical procedures or AI/ML methods, each field sensors can be characterized individually. The choice of which method to apply to develop individual correction function depends on the knowledge level of the sensor characteristics: In case the characteristics, such as temperature dependency, are well known, statistical methods could be sufficient to derive the correction function. However, if the dependencies are not well known, or if sensor sensitivities are mutually dependent, it can be difficult or impossible to derive analytical correction functions. In such cases, AI/ML methods are better suitable to characterize the sensors.

Experts especially working in the field of AI, responded positively for the idea of AI integration to improve CS AQ data. The results (see section 4.4) demonstrate that to make the calibrations more precise, deep neural networks can be applied. Calibrating data, that is data correction and validation, to increase accuracy is the most significant step in data analysis, keeping in mind that the sensors that are deployed are low-cost. AI data mining methods and outlier detection algorithms are also used to achieve more precision in the values of these measurements by sensors. Moreover, the fact that citizens have the power of contributing to these air quality measurement tasks, would be beneficial because the volume of data is upsurged. However, even though the large volume of data collected, the quality has to be ensured.

A further novel finding is the advances in ML that help recognise and eliminate data 'noise' caused by glitches (Zevin et al. 2017), Experts also mentioned AI and ML models such as anomaly detection algorithm, Gaussian Model for regression, ARIMA (ML algorithm), ODE, SDE as explained in section 4.4.2. Results also demonstrate an important aspect of the process of the pilot in which these AI/ML methods could be integrated, which are, data analysis, location and geospatial optimization, and spatial resolutions (particularly for earth observation data). With the production of coupled devices and up searched data collection, AI technology has the aptitude to sensationally impact society, which includes businesses and the workforce (Ceccaroni, 2019).

To conclude, for all the known potentials of AI, it possesses limitations as well. This includes the lack of social acceptance, the explanation of the results from large and complex models in human terms, and the risk of bias in data and algorithms (Schade, S. et al. 2020). Simultaneously AI is a vital tool for accelerating CS AQ data ultimately to immensely scale scientific research. As the role of AI grows, humans progressively count on machines to complete errands, which makes it crucial that the CS community must be made aware of the ethical considerations of AI (Ceccaroni, 2019). Therefore, a mixed integrated system of human intelligence and computer intelligence must be adopted to overcome the complexity of analyzing the data.

Sub Question 2: Which factors stimulate or hamper AI integrated CS for AQ assessment?

Socio-technical factors have a major influence on the relationship between AI and its integration with CS AQ data. According to the research findings, these factors act as a mediator in stimulating this relationship. The social factors like citizen' participation and behaviour, citizens' perceptions and individual conditions were evaluated. Apart from this, the technical factors, including technique usability, network and organizational structure is also measured. The results from the analysis presented in section 4.5, established interlinked relationship between these factors which play a significant role in CS AQ assessment projects. The experts had similar opinions about the unreliable data quality and mentioned that working with citizen science data implies accepting that the data is not of high quality, but that it can still be utilized. The use of manual statistical techniques has till now been able to achieve the required results, however, these methods are rigorous and labour-intensive. Besides, identifying the non-linearity of the data sources is also a challenge with these physical statistical techniques.

Another challenge as per the results were the components of air pollutants and the nature of their measurements. For instance, the NO_2 measurements are not reliable according to the experts (see section 4.5.4). This highlights the questions from the organizations perspective about displaying this data as it raises questions from the participants' perspective. As it's the citizens who are the owner of the data, it should be fully accessible. And if the data is not reliable, then it's something they should be able to see for themselves. Sometimes, the peaks in the measurements would also be influenced by the humidity and wind direction which also increases the overall complexity of the process.

Collectively, the results appear consistent with the survey conducted by Waag, from which it can be concluded that Hollandse Luchten has been able to reach a large group of active and involved participants. Of the 60 participants who completed the questionnaire. 92% want to remain involved in the project. Valuable feedback and information were received from the survey, which is used in combination with other forms of evaluation to further develop the project. Additionally, the project had a positive impact on knowledge and insights (54%) and the feeling of having one stronger substantiation in conversations about air quality (65%). Besides experienced, 44% of the participants view the data as usable. Also, the spread of more attention and awareness on the subject and the associated problems and issues in the immediate vicinity is important and should be the first step in creating more attention for a healthy living environment (57%). ***Most criticism and feedback were about the need for more tools, more interpretation of the data, and communication to and within the network***.

Citizens' collection of data ought to be validated, which is usually problematic for professionals and research scientists. Current applications of AI provide methods like data mining and deep learning technology that can analyse large amounts of data from numerous sources. Additionally, to expand the accuracy rates of the acquired data, citizen scientists can be involved to guide algorithms. AI proves a very effective tool for appealing and connecting people to science (Ceccaroni, 2019). AI is beneficial for the amateur participants (people with less or no experience in the field), by being trained in coaching computers, which creates a more comprehensive, stirring and impactful scientific practice. Some organizations are training AI algorithms on huge amounts of former data and observations composed by scientists and citizens universally. AI tools especially deep learning can be combined with massive scale CS data to improve unknown AQ data sources. Sullivan et al. (2018) speculate that a commonly used approach to harness the brain processing power of humans will include the integration of scientific tasks into reputable computer games. This will use the intricate designs of CS games that could directly feed or train ML models, for instance, reinforcement learning, through which large scale data can be computed with minimum errors.

CS often is perceived as a job as a result of the passiveness in decision-making and citizens' distrust on the government. But a much bigger problem for CS is the other way around. The big challenge is to get organizations to trust the citizens' data and its validity enough to produce reliable results. This not only influences the citizens' participation and motivation but also their perception of data quality. Trust could also be a factor, for instance, if the traceability of the analysis is not evident. The research findings from the interviews of the community leaders also portrayed a lack of trust in the organizations and desired more transparency with data analysis and interpretation (see section 4.6.4). AI methods could also address this problem if the tools are used considering the Trustworthy AI, which ensures more transparency and systematic documentation of all operations.

Sub Question 3: How and to what extent did these factors impact the AI integrated CS for AQ assessment?

Empirical findings suggest that examining socio-technical factors to integrate AI for CS AQ assessment is the most fundamental need to enhance CS AQ data. Information provision about self-measurement, the quality of the measurements and the interpretation and reliability of data are of great importance. By combining self-collected data with growing knowledge about air quality, citizens will become a stronger partner for government and companies, making for more constructive and smarter solutions. These measurements are added to the official measurements. The goal always is to generate financial capacity from below so that citizens can measure air quality themselves in the long term, instead of this action being carried out by official bodies.

Simultaneously, the social factors, especially, citizens' motivations, behavior, participation and perceptions, were highlighted as stimulating factors in a volunteer participation cycle (Yadav and Darlington, 2016). Some people are involved because they feel that the community is polarized, which is a major motivation for them to be defensive of the Tata Steel factory. Participation against this polarization uplifting a sense of social influence in their neighborhoods. On one hand, this highlights a social reason to participate, whereas, on the other hand, people are also motivated because of the technical curiosity and knowledge sharing environment. This encourages the community to have the measurements, so that at least the facts can be drawn, to ignite a discussion. Some people are really worried about their health, the health of their children, or, they have health problems themselves.

The results of the findings also highlight the importance of CS. After all, the monitoring network of other numerous official monitoring stations has a high cost for public organizations, because very expensive and very precise devices are the perquisites in such processes, that require installation by experts. These incur large maintenance costs. CS not only enables a large volume of data but also democratize this task of monitoring. This inevitably affects CS AQ data.

AI is a powerful tool that can progressively improve performance on a specific task (Ceccaroni, 2019). However, if access to AI resources is constrained by commercial interests, citizens (especially scientists) may be excluded from significant decisions including policies that directly impact their lives. As the interaction between humans and computer changes, for instance, the progress of ML, CS projects will evolve in methodology and organization. AI methods can also be used to improve data accessibility and communication. Apart from addressing the data quality issue, AI tools should also address the processes and services that generate and exchange data between any two parties. Such tools increase interoperability to exchange data with ambiguous processes, improve quality, efficiency and efficacy.

5.3 Recommendations for Future Work

Analysing the opportunities and risks of AI in CS AQ assessment is novel and challenging. Both CS and AI are not established science. Both require practical analysing than belonging in textbooks. Therefore, AI integration with human social context has its limitations.

The procedures of engaging citizens in scientific research are required to be aligned with the approach and vision of what *good data* is. Future research could focus on determining the optimum location of sensors, especially while combining earth observation and citizen sensing data. The results also showed evidence for optimizing the location (Gupta. et. al 2019) for the deployments of these low-cost sensors to be able to collect observations, at a very fine spatial resolution. It also means that applications can be developed for this fine resolution because these observations can be representative of, for instance, 100 to 500 square meters, if the location is properly chosen. In this case, assuming that a sensor is next to a Boulevard or an avenue where these sensors are deployed, all these observations in this avenue can be measured. Assuming it's an avenue which is very popular for runners or some sort of sporting activities, it could be recommended, to each citizen passing by what is a proper time to go for a run. And the amount of pollution that is inhaled at what amount of time. So, that is probably a good or reasonable time slot to recommend this activity. This could be also an advantage of these fine resolution monitoring, find resolution applications as well or recommendations. Another benefit of fined scaled AQ observations is the data can be used for modelling AQ condition. This allows AI ML methods for modelling improvements, for example, to train the model about local micrometeorological conditions that affect local chemical processes and concentrations of air pollutants.

As the list of the application grows, so does the awareness of AI in our lives. Another important factor to consider in the realm of AI is the public perception of AI (Hecht 2018). This is to increase the social acceptance of citizens towards technology. For this purpose, the social and behavioural context of participants should be measured before and after the process of using AI applications. Behavioural change and cognition are a crucial social factor that has to be analysed simultaneously with technology to impact or increase social inclusion in society. Clear conclusions can then be drawn with multiple measurements at the beginning and end of the project.

“The future of citizen science lies in coordinating people, projects and data, drawing on co-creation to facilitate mutual agreement” (Ceccaroni, 2019, p.8). CS data can act as sensible evidence for “various decision-making processes that impact citizens’ lives and surroundings, including environmental policy” (Hecker et. al 2019, p.151). However, appropriate management of data, especially, when it comes to data reliability, that can fulfil their roles of empowering communities, must be considered. To maximise the impact of CS data, CS projects should adopt AI methods and tools that enable data reusability across platforms and stakeholders and increases data quality and accuracy. Consequently, CS will be able to intensify and reach its remarkable potential for progressing environmental research for a project like Hollandse Luchten.

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Annex 1: Research Instruments

<u>Semi-structured Interview Guide with the Experts</u>

My name is Soumya Sood. I am a Master student in the IHS at Erasmus University, in Rotterdam. This research aims to investigate the if artificial intelligence can facilitate citizen science air quality data as well how socio-technical environment affects the performance of citizen-led- AQ projects in North Holland. I am interviewing you because of your expertise in the Projects Sentinel Citizen and Hollandse Luchten. This interview is intended to support data collection for academic purposes. With your permission, I would like to record our conversation to enable my analysis after this. Please be assured that all the information provided by you will be confidential,

Introduction

1. How long have you been working in the field?
2. Can you tell me about Sentinel Citizen and Hollandse projects? (if applicable to the expert)
3. How long have you been working in the field? (AI/ CS AQ)

Artificial Intelligence

Technical

4. How is accuracy is measured and assured?
5. How is the system's reliability assured?
6. Is there an explanation to why a certain choice resulting in an outcome was made by the system that all users can understand?
7. How Is the communication with the end-users assured?

Social

8. What is the strategy to avoid unfair bias in both the input data and the algorithm design?
9. How is the AI system made accessible for universal design to ensure inclusion?
10. Is there a measure to reduce the environmental impact of the AI's system life cycle? Explain how?
11. Is there an assessment of a social impact of AI system on the users? Explain how?
12. Is there respect for privacy and protection of personal data by the system? Explain how?

Case Study (Hollandse Luchten)- If applicable to the expert and specific questions depending on the field of the expert will be asked.

13. Can AI/ML models be integrated into CS AQ projects? Explain how?
14. Can AI/ML models be integrated to improve the quality of CS AQ data? Explain how?
15. What are the challenges faced by you regarding AQ data?
16. What are the challenges faced by you regarding Citizen Science?
17. What is done to ensure the continued participation of the citizens?
18. Did you notice behavioural changes in citizens regarding air quality? Explain how?
19. How have the perceptions of citizens differed from before and after the project?
20. How is the quality of AQ data ensured?
21. What are the benefits of citizen science in air quality monitoring?
22. What technical changes or altercations would you suggest in enhancing the projects?
23. What are your views regarding the effectiveness of these projects?

<u>Semi-structured Interview Guide with the Citizens</u>

My name is Soumya Sood. I am a Master student in the IHS at Erasmus University, in Rotterdam. This research aims to investigate the if artificial intelligence can facilitate citizen science air quality data as well how socio-technical environment affects the performance of citizen-led- AQ projects in North Holland. I am interviewing you because you participate in the Projects Sentinel Citizen and Hollandse Luchten. This interview is intended to support data collection for academic purposes. With your permission, I would like to record our conversation to enable my analysis after this. Please be assured that all the information provided by you will be confidential,

Introduction

1. How long have you been living here, specifically in this area?

Participation and Behaviour

2. What type of citizen engagement projects have you been involved in?
3. In what ways are you involved in the projects?
4. What motivated you to be a part of the project?
5. Will you continue to be a part of the project? Why?
6. What impact did the project leave on you?

Individual Conditions

7. How much time do you dedicate per week as a participant?
8. What other resources are required o to be a continuous participant?
9. What resources are provided by the researchers to you?
10. What constraints do you face for being a continuous participant?
11. Is there a social impact in the neighbourhood? Explain how?
12. Does social media make an impact regarding the perception and behaviour of the people towards improving air quality? Explain how?

Data Collection

13. Did you face any difficulty with the devices?
14. How is the quality of the online platform?
15. Is there any difficulty faced by you regarding the technical side? Please explain.
16. Are the researchers and the data easily accessible when needed? Please explain.

Communication

17. Which technical features related to project keep you involved?
18. Which technical features need upgradation according to you?
19. How is the whole network of operations of this project according to you?

Conclusion

20. What is your opinion regarding the process of the program?
21. Do you perceive any changes in the perception of people? What are your opinions on the CS and AQ projects?

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