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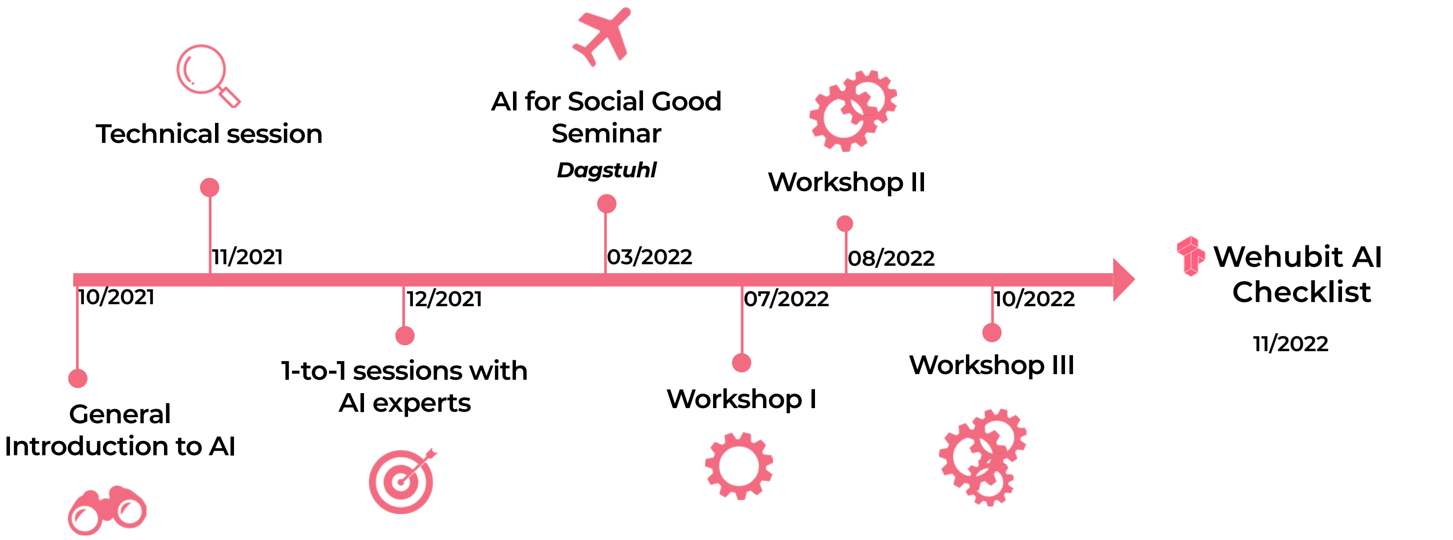
WEHUBIT ARTIFICIAL INTELLIGENCE CHECKLIST

What are the preconditions to start implementing a digital social innovation using machine learning*?

In 2021, Wehubit began a trajectory of exchange and capacity sharing around **artificial intelligence** (AI), in collaboration with AI for Social Good Dagstuhl Seminar. Three organisations have been at the end of this trajectory: **D-tree International**, **TechnoServe** and **AirQo**.

What to take away from their experiences? After three online workshops, the Knowledge Exchange Network (KEN) first Working Group publishes a checklist on the prerequisites for implementing **digital innovation using machine learning***!

** **Machine learning** is a subset of artificial intelligence and computer science which focuses on the **use of data and algorithms** to imitate the ways humans learn, gradually improving its accuracy. Through the use of statistical methods, algorithms are trained to make **classifications or predictions**, and to uncover **key insights from data.***



AI on the Wehubit E-library

The digital version giving access to the different links is available on the following link: www.wehubit.be/e-library

- Artificial intelligence and the circular economy: AI as a tool to accelerate the transition
- Artificial Intelligence in Global Health: Defining a Collective Path Forward
- Ethics and Governance of AI for Health
- Towards a research program Artificial intelligence and human development
- Managing machine learning projects in international development a practical guide
- The AI Ethics Playbook Implementing ethical principles into everyday business
- Report from Dagstuhl Seminar

PROJECT 1: DRONE-ASSISTED LAND MAPPING FOR CLIMATE SMART CASHEW PRODUCTION – CAJULAB

The CajùLab project analysed cashew areas at national level – by **identifying cashew areas** and developing a state of play of the cashew sector – and **plantation level** – by identifying **crop health** and **land management practices**. The objective was to provide information on the cashew sector through quality data, and therefore **enable policymakers** and **training services** to **adjust resources** and **services to small scale farmers**.

The project worked with **drones** and **satellites imagery**, analysed through a **deep learning structure** *. This structure used both texture information - what the **cashew tree looks like** - and temporal information - how the **cashew tree changes during its growth period** – to identify cashew trees and **farming/land management practices** (examples : cashew trees from other species, density of trees).

BENIN

By TechnoServe

From 06/2019 to 09/2021

SDGs 2 ZERO HUNGER 13 CLIMATE ACTION

€349.238

More information?
Discover their Learning Sheet

This data produced was valued and disseminated through:

- An **online remote sensing dashboard**, designed for policymakers and training providers
- An **Action Plan on Climate-smart Cashew Production** to scale up sustainable farming practices among 11,000 cashew farmers

* ***Deep learning*** *is a subset of machine learning. Deep learning can analyse* **images, videos, and unstructured data** *in ways machine learning can't easily do.*

PROJECT 2: USING MACHINE LEARNING TO PERSONALIZE AND IMPROVE PERINATAL HEALTH IN ZANZIBAR

The objective of the project was to support **Community Health Volunteers** (CHVs) to identify **pregnant women with an estimated high risk of perinatal complications**, in order to provide them with additional, targeted household visits to discuss **risk factors and mitigation strategies**.

When a CHV identified a new pregnant woman in the catchment area, he/she enrolled her – after receiving consent - into **Jamii ni Afya**, **Zanzibar's National Community Health program**, using a smartphone app. The CHV collected **demographic data, data about past pregnancies and health conditions** and, based on the collected data, a machine learning model estimated whether the **woman is at higher risk of experiencing child death during the pregnancy**. The model output is not communicated to the CHV or pregnant woman as such. If it estimates a higher risk, the app schedules additional visits.

TANZANIA

By D-tree International

From 12/2019 to 05/2022

SDGs 3 GOOD HEALTH AND WELL-BEING

€349.887

More information?
Discover their Learning Sheet

PROJECT 3: SCALING UP A PARTICIPATORY AND CITIZEN-DRIVEN AIR POLLUTION SENSING AND ANALYSIS SYSTEM FOR URBAN RESILIENCE IN UGANDA - AIRQO

The AirQo project aims to provide **timely** and **hyperlocal access** to air quality information for **urban dwellers and policy makers** in Ugandan cities, allowing them to take actions that lead to **improvement of air quality** in their communities. **80 sensors locally designed** and built at Makerere University have been deployed (will be increased to **150** devices at the end of the project) collecting near-real time air pollution data.

More information?
Discover their webpage
or their app

UGANDA

By Makerere University

From 04/2021 to 03/2023

SDGs

€342.000

The data are disseminated through an **air quality web platform and mobile app**. AirQo integrates machine learning in its products for:

- **Spatial temporal predictions**: machine learning is used to forecast what the air quality will be in the next 24 hours in order to inform **individual decisions to minimise exposure**. The forecasts are available for all active monitoring sites on the AirQo network but machine learning is also used to **predict/estimate** what the air quality levels are in locations around the cities, without air quality monitors at specific times. These predictions are used to generate **heatmaps** that help authorities understand the spatial temporal variations acrosss the city.

- **Sensor data calibration to improve data accuracy**: machine learning models are used to calibrate data * from low-cost air quality monitors to improve their **accuracy, reliability** and to ensure that their readings are as close as possible to the **international reference standards**. The machine learning calibration model is now also a product that can be used by anyone to calibrate low-sensor data. Learn more about how AirQo is using machine learning for calibration in their recent research paper.

- **Sensors placement optimisation**: machine learning is used to provide recommendations for **optimal sensors placement**.

* ***Calibration*** *refers to the process of comparing and correcting device measurements against outputs from* ***internationally accepted standard reference devices****. Calibrating data makes the measurements from devices more accurate and reliable.*

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This following checklist aims to inform and support project managers or teams that consider ***introducing machine learning*** *to support (part of) their organisation's activities.*

It lists ***9 important issues*** *that were collectively raised by the concerned Wehubit projects, illustrated by their* ***own lessons-learned*** *regarding three key aspects that need to be in place before introducing AI:* ***Organisations; Data;*** *and* ***End-users & final beneficiaries****.*

ORGANISATIONS

1. Conduct a pilot phase and test a proof of concept

Implementing a digital innovation with a machine learning component requires a careful preparation for several reasons. First and foremost, a pilot phase, in which a **proof of concept is tested in the local environment** should be planned for. As AI is still relatively new in the context of international cooperation and deals with a large amount of data, it still **raises questions**. Projects need to give evidence for the potential that machine learning tools have to **leverage change in diverse sectors** and **to show its added value**.

Depending on the sector and project, proofs of concept can have different dimensions and objectives – what do we need to show? In addition to the general objectives of a proof of concept, demonstrating viability and feasibility, conducting a pilot phase for an AI project therefore helps to build **trust with stakeholders** – especially governments – and **secure their buy-in from the start.**

Pilot phases also enable projects enable projects to better assess **resources required for successful implementation**, and to better understand, prepare and process the data to fit the needs of the machine learning model.

D-tree *developed a machine learning model based on data representing the whole country. However, it started with a small pilot in two of the eleven* ***Jamii ni Afya districts****, to give evidence that the machine learning model in addition to Community Health Volunteers (CHVs) intervention was* ***effective****.*

The proof of concept needed to show that the predictive model ***could run offline on a low- to mid-resource phone*** *and could be used to target a* ***health intervention****.*

The evaluation shows that machine learning could be used successfully, although there was no statistically significant difference in the use of the ***model combined to CHVs work****, or the* ***work of CHVs alone****, i.e. the use of machine learning didn't lead to care improvement.*

2. Recruit staff in-house able to speak both thematic and technical languages

When it comes to finding the right skills, the first step is to identify the **compentency needs** and **the gaps** to be filled. To be successful, the project will need thematic and technical expertise, and staff that will be able to "speak both languages"; usually **data scientist(s)** or **computer engineer(s)**, who will guide the project and have a generic view.

Staff linking thematic and technical matters is preferably in-house staff. This staff is responsible for ensuring that the machine learning model(s) developed **fit(s) the needs** of the project: they can **undertake internal** and/or **external technical discussions** to steer the project and can be a **common focal point** to the diverse groups of stakeholders.

3. Secure technical skills, based on long term strategy

The decision to acquire technical staff/skills needed to develop and manage the machine learning model(s) in-house or to secure those skills through partnerships should be linked to the **organisation's long-term strategy**. Three main aspects should be considered: (1) the **organisation's plans to continue working in a specific sector** (2) the **sensitivity of the data in this sector** (3) the will to invest in and keep working with **machine learning components to achieve the organisations' aims**.

Alternatively, partnerships with **universities** or **organisations specialised in machine learning** can be established to **secure technical skills**. All three Wehubit projects working with machine learning relied on **human resources from international** and **local universities**. There are several advantages working with them:

- It's a win-win collaboration as universities are looking for **opportunities to «test» their work**, act as knowledge centers and publish.
- The data and digital tool(s) are either owned by the project or the universities themselves, ensuring that students will be able to continue **developing and adapting the tool** in the long-term, thus ensuring **ownership** and **sustainability of the digital tool(s)**; which may not be the case with the private sector (see Data ownership below).
- It builds local skills and allows for the **development of a digital ecosystem**, by involving over time several students, thus creating in-country a **critical pool of people** with machine learning skills.

*The **AirQo** team is based within Makerere University – Kampala. All technical staff, including the air sensor production unit and the AI experts, is **in-house staff**, some of them former students and interns. For AirQo, having the staff in-house allows for more **flexibility** and **adaptability**: The team is **ready, informed** and **trained**, whenever there is a change to make or maintenance to perform. Externalising all maintenance work would also be more costly for the project.*

*AirQo remains a **learning** organisation and still leverages on external knowledge exchanges.*

- *It leverages on **students networks**, including them in reflections (e.g. Organisation of Hackathons) or taking them as interns.*
- *It works with **external actors** in formal or informal partnerships and mentorships, such as Google Deep Mind or Sheffield University.*
- *It uses open **machine learning community platforms**, such as Zindi. This platform allows exposing an issue and discuss solutions with the community, **getting feedback and gathering knowledge**. Regarding its forecasting model, AirQo developed something internally before posting challenges on Zindi. After evaluating the top three solutions, it incorporated these into the model.*

*__D-tree__ partnered with **N/LAB**, a centre of excellence in behavioural analytics at the **University of Nottingham**. N/LAB built the machine learning model and supported D-tree in adapting it for use in the CHV app. During the course of the project D-tree also built in-house capacity, but still sees value in engaging with external partners like N/LAB, especially for cutting edge machine learning techniques that **require very specialised expertise**. To further sustain machine learning solutions locally, including beyond D-tree's work, D-tree is **now starting to partner with local universities**.*

*__CajùLab__ partnered with universities to find the **technical skills needed**.*

*As the machine learning domain is not yet well developed in Benin, CajùLab partnered with the **University of Minnesota** to develop its algorithm.*

*Regarding the development and maintenance of the friendly-user dashboard – used by state agents and training services – CajùLab initiated a collaboration with the **University of Parakou and Institute of Mathematics and Physics Science of Dangbo.***

*In order to partner with a local university, CajùLab has carefully analysed the local context of implementation and identified universities with a dynamic **IT department**, whose professors were willing to get involved. It trained the IT students about development and maintenance thus allowing for skills transfer and **local ownership** of the digital tool.*

DATA

4. Check local laws as these serve as a legal framework for data governance * and privacy

Investigating whether the local legal framework of the implementation country regulates **data governance and privacy** is a must, especially if operating in a **fragile context** and/or **with sensitive data**. There is a risk when implementing a project including machine learning with no legal grounds regulating data to be **shut down by the government because of distrust**.

If there is no legal framework in the country of implementation, the project can work to **build an enabling environment and trust**. First and foremost, it is important to have some kind of **agreement** with – well identified - **state actors** and/or **the government**, and make sure that they support the project. If trust is well established with state partners, it can also eventually allow for **lobbying for a legal framework**.

Another element that can support an enabling environment and trust, is the reference to **formal or informal frameworks**, **laws** and/or **good practices**, which can come from the national, regional or international level. This can be used as a basis to develop an internal (organisational level) framework according to which the **data are regulated**.

* ***Data governance*** *has many definitions and is viewed here as formal or informal institutional* ***arrangements regulating data ownership****; the* ***procedures/protocols for data collection, storage, access, and sharing*** *- and the* ***process to decide over these procedures and to monitor them*** *- ; data privacy and security; the practice of ensuring that data can be used effectively by the people who can extract value from it, while individuals' and communities'* ***rights to privacy are respected at all times.***

Because of the sensitivity of health data, ***government partnership is essential****. However,* ***D-tree*** *implemented the Wehubit project in Tanzania, where at the time of project implementation, there was* ***no legal framework regulating data****. During the course of the project, it created its own framework that specified data governance , and how to monitor adherence to the framework and hold* ***stakeholders accountable****. D-tree worked closely with government partners (i.e. the program manager counterparts together with the line managers up to the Principal Secretary) to ensure that the framework was in line with their expectations. Additionally, it submitted a* ***proposal to the National Ethics Review Board*** *(with government program partners as co-investigators).*

AirQo *adheres to local and regional regulatory frameworks such as the* ***Data protection*** *and* ***privacy act*** *of Uganda. It's a reference tool to ensure stakeholders' data is secure. In terms of concrete implementation for example, to preserve the privacy of individuals and institutions hosting the monitoring devices and potential misuse of devices, actual coordinates where the air quality monitor is installed are remotely adjusted so that the* ***monitoring area is known without revealing the exact location of the monitor****.*

5. Define clear guidelines on *who does what* regarding data ownership, data use and data privacy, that you can share and agree upon with stakeholders

In addition to a legal framework, it's important to have a clear agreement with the government and/or other stakeholders about **data ownership, data use** and **sustainability**. These need to be addressed and **mutually agreed** upon before the project starts.

Especially when dealing with personal, sensitive data, a **clear agreement will ensure responsible use of data**, in line with the "do not harm" principle. This agreement also ensures **transparency** to the users and people whose data are collected.

*AirQo owns the air quality data, however it's available freely to any one by requesting and accessing it through the **platform** and consenting to the **data usage agreement**. Additionally, it can be accessed by anyone with some of AirQo's other platforms e.g. mobile app, website and the **API** (application programming interfaces). The user of this data, as part of the data usage agreement, is required to **credit /reference/give attribution to AirQo as the original primary source**.*
*In addition, AirQo has developed Memorandums of understanding with their partners and project's stakeholders (UNEP, Kampala capital city authority, ministries...), where they agree, among other things, on **information sharing and data confidentiality**.*

*D-tree already had full ownership over a **historic data set**. However, during the Wehubit projects lifetime, they couldn't formalise ownership with the government about the current data set (i.e. data from the government s'National community health program) as there was **no data sharing framework**. This inhibited the model update during the project.*

*The Government of Benin had a **legal framework for data governance**. Based on this, TechnoServe developed an internal Data privacy policy, incorporating the **dashboard** and **more specifically usage data**. However, data collected through drones and satellites mapping - such the **name of the plantation owners, their locations, their yields** - are not yet included in their Data privacy policy.*

6. Assure that the data set is inclusive and address possible bias

Projects should try to obtain the **most representative data** set with regards to the scope of the project and **leave no one behind**. This means that **underrepresented groups should have equal opportunity to be included** in the project and data sets should - as much as possible - enable identification of such groups and allow evidence-informed actions to improve their situation. If the project cannot guarantee a **comprehensive coverage** and even if underrepresented groups have been taken into account, the risk of potential bias should be considered and **regular discussions among partners** on how to address these biases need to be held from the start of the project.

*One issue was the struggle to take hard-to-reach people into account in order to be as **inclusive and representative** as possible. Regarding biases, even if D-tree was aware of them, they were hard to address. For example, D-tree collected data regarding proxy variables for socio-economic status (e.g. roof, floor material), but was not yet able to evaluate other predictors of **health-seeking behaviour that address some weaknesses of socio-economic status models**.*

*For its air quality monitors, **AirQo** chose representative sites that capture the various variations of the physical environment, such as **population distribution** (e.g. high population density vs low population density; commercial vs residential areas), land use, upscale vs informal settlements...*

*AirQo has provided information to the **local authorities and communities** about the location of air quality monitors to allow for the diverse stakeholders to aknowledge the gaps and think about possible solutions. **Stakeholders' engagement and discussions** on the issues at hand help create synergies and open up room for further **interaction and more inclusion**. E.g. while scoping and deciding where to place air quality monitors, AirQo collaborates with the local leadership team.*

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*While developing their dashboard and deciding which crops to map and analyse, **CajùLab** used **farmers' registration databases** and **TechnoServe's annual yield surveys**. It turned out that the percentage of **women owning cashew nut plantations was quite small compared to the men's percentage**. This indicated that women have limited access to land and registration databases are developed based on land ownership (and not land use).*

7. Assure that the data is accurate, consistent and valid

For the machine learning model to be of any use, data collected must be of **high quality, usable** and **fit the needs of the model**. This includes:

- Data will allow the model to reach a high level of **accuracy**. Meaning that the measures taken correspond to what **is supposed to be measured.**
- Data have no outliers, collected data are in the expected range of value. The **expected value range of value is defined before starting data collection processes**.
- Data set is large enough to be representative. To make valid predictions, the data set must be large enough to represent all possible scenarios for which forecasts will be made, with sufficient **characteristics and quality.** The model must be able to compare the possible scenarios.
- Data come from a **trustful source**. They are complete and should allow for a high level of accuracy. Data sources should be re-usable and complementary.

*When running a machine learning model, the source of the data to be used is important to get a **quality data input**. For drone data, **CajùLab** has partnered with an organisation named AtlasGIS in the **collection of drone images**, which strongly helped to assure quality plantation drone images. In the case of the ground & yield data, CajùLab, through the BeninCaju project's Monitoring and Evaluation team, has gathered this information through **yearly surveys in all intervention zones of the project.** CajùLab chose PlanetScope microsatellite constellation with high resolution and rapid revisit (less than 1 day) as **data source**. Data privacy is one of the key aspect of the CajùLab project because they are dealing with personal information of the cashew producers across the major production zones of cashew.*

***D-tree** approached data quality in three different ways: (1) The CHV app is designed with **data format checks** and **data validation rules;** (2) Outliers are **monitored** (e.g. fast or high number of visits during a short time); (3) **Regular data quality assessments are conducted**, where spot checks are done to verify with households whether they have actually been visited by a CHV and confirm the collected information. Additionally, a data set goes through **data cleaning before being used as input for machine learning modeling**.*

*Collected data go through **multiple stages of data validation** and **cleaning**, starting from the lab where devices are developed – at **Makerere University**. Quality assurance is performed to ensure that devices all meet the set-out criteria before they're **deployed into the field**. Afterwards, raw data collected goes through a serie of data quality checks before being accessible through the platform and before being used for **machine learning modeling**. These data quality checks include outliers and out-of-range values checks, dual sensor correlation checks, calibration to ensure the data set meets reference grade standards. In addition, **continuous maintenance** of the air quality monitors is carried out by the AirQo team.*

END-USERS AND FINAL BENEFICIARIES

8. Define your end-user(s)

Who is going to make use of the results produced? **Researchers? Policy makers? Communities? And who is the priority target?**

Different end-users require **different ways of communication about the results** that a machine learning model produces, if these are to be used for activities/further research. It is therefore important to clearly **define the end-users as it enables to:**

- Assess their **needs** , including in terms of **digital and data literacy**, and design the tools accordingly;
- Plan for their possible **capacity sharing** in order for them to be able to use the information produced;
- Include them in the **project design and implementation** and ensure a better fit between results of the machine learning model and the development of **appropriate solutions;**
- Adapt the **language** that the project uses and develop different communication strategies;
- Build trust and ownership through appropriate **communication at all stages of the intervention**

For each project, the priority end-user was different from the final beneficiaries. This implies that there have been different strategies for the end-user and for the final beneficiaries on **how and when results were presented to be actionable** and **trusted**. For example, a prediction based on machine learning and its derived recommendation could be presented with "**a level of confidence**" to end-users, based on false/true negatives expectations. At beneficiaries level, the solution could be designed as to work on the prediction without mentioning it, while eliminating/reducing harmful effects.

The cashew farmers are not the end-users of the digital social innovation but the ***final beneficiaries****. The dashboard - the results produced - has been used by* ***technicians from the Ministry of Agriculture*** *to inform decision-making and by training providers and cooperatives to tailor their support to farmers.* ***TechnoServe*** *also expects researchers and students from the* ***University of Abomey-Calavi to use the dashboards as data source for their research studies on cashew in Benin****.*

Identifying those end-users allowed for a needs-driven platform development (what kind of information is needed for what ?) and for appropriate capacity sharing on digital and technical aspects.

D-tree*'s end users include CHVs, CHV supervisors and decision makers at district and central Ministry of Health level. CHVs and supervisors use the digital app, while* ***decision makers only use the outputs.*** *CHVs are the priority end-users, and they receive initial training, refresher training, as well as* ***continued support through peer mentors*** *and* ***supervisors****. CHVs are not trained health professionals, and thus the app provides them with decision support and standardised messaging to* ***pregnant women.***

AirQo*'s main end-users include decision makers and local leaders who are directly involved in policy. They use the platforms to* ***guide policy generation****.*

Final beneficiaries (communities, citizens) are also involved in some activities of the project i.e. ***problem formulation in context, data collection, evaluation*** *and* ***deployment****.*

9. Assure suitability of Artificial intelligence/machine learning for the identified issue and assess the risk of unintended negative effects

Machine learning has great potential, but a large data set and a worthy objective may not be enough to **develop a fit for purpose model while respecting the "do not harm"** and **"leave no one behind" principles**. Machine learning tools have to be assessed carefully according to the field of research and the **issues to be addressed**, answering these questions:

- Will it be possible to have **high accuracy**? (number of true positives and negatives divided by population size)
- Will it be **precise**? (true positives divided by predicted positives)
- Will it have enough **sensitivity - or recall**? (true positive that are correctly identified)

And thus, does the added value outweigh the risks and potential bias, especially regarding **final beneficiaries**? Will the output of the algorithm be actionable, e.g. can it trigger an effective intervention?

*The machine learning model output by **D-tree** is simply «estimated higher risk» or «no estimated higher risk». The main challenge faced by the project was the **high number of false positives**. The model was calibrated for a low number of false negatives, to not miss women who **actually experience perinatal child death**. Consequently, the number of false positives rose.*

*To not introduce negative side effects to these women (e.g. getting unnecessarily anxious about a potential child death), the **model output (i.e. risk prediction) is not communicated to CHV** or **pregnant woman.***

*In addition, a manual risk assessment was conducted, where the CHV goes through a list of relevant health conditions and other questions. The manual assessment was included to **safeguard against biases** or an otherwise badly performing machine learning model.*

***AirQo** always provide uncertainty quantifications and confidence levels while **communicating the results from the machine learning models.** In addition, when sharing the results with end users or final beneficiaries, AirQo will provide dispassionate thresholds. For example, instead of pointing out that a certain place is the worst polluted place, it will refer to **World Health Organisation's recommended levels**.*

*This learning sheet has been developed in the framework of the Wehubit Knowledge Exchange Network in collaboration with
Heiko Hornung, D-tree,
Richard Sserunjogi, AirQo
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