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Promoting sustainable and personalised travel behaviours while preserving data privacy

Noela Pina[a], Cláudia Brito[b], Ricardo Vitorino[a], Inês Cunha[a]

[a]*Ubiwhere, lda., Travessa Senhor das Barrocas, 38, Aveiro, 3800–075, Portugal*
[b]*INESC TEC Universidade do Minho, R. da Universidade, Braga, 4710-057, Portugal*

Abstract

Cities worldwide have agreed on ambitious goals regarding carbon neutrality, thus, smart cities face challenges regarding active and shared mobility active and shared mobility due to public transportation's low attractiveness and lack of real-time multimodal information. These issues have led to a lack of information of the community's mobility choices, traffic commuters' carbon footprint and corresponding low motivation to change habits. Besides, many consumers are reluctant to use certain software due to the lack of guarantee of their data privacy. In this paper we present a methodology developed in the FranchetAI project, that addresses these issues by providing distributed privacy-preserving machine learning models that identify travel behaviour patterns and respective GHG emissions to recommend alternative options. Also, we present the developed FranchetAI mobile prototype.

Keywords: Emissions monitoring; Citizens engagement; Data Privacy; Artificial Intelligence; Sustainable cities and communities; Multimodal transport;

1. Introduction

According to the World Economic Forum (WEF, 2022), ”mobility is a fundamental human need, and an essential enabler of prosperity, but the current mobility paradigm is not sustainable”. Quoting WEF, car travel causes millions of deaths every year, with a significant amount of Greenhouse Gas (GHG) emissions being transport-related and congestions causing heavy financial losses. The global mobility system is in the early stages of massive transformation worldwide, as novel technologies enable innovative related businesses. Moreover, policymakers seek out ways to foster mobility that becomes smarter, cleaner, and more inclusive. The European Commission also acknowledges that transport is the leading cause of air pollution in cities EC (2016). Cities worldwide have agreed on ambitious goals

[*] Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000.
E-mail address: author@institute.xxx

towards 2030 regarding GHG emissions and carbon neutrality. Based on that ambitious roadmap, smart cities face challenges regarding active and shared mobility due to public transportation's low attractiveness and lack of real-time multimodal information for citizens (that integrates public transport). These struggles have increased the community's lack of awareness of their mobility choices' carbon footprint and corresponding low motivation to change habits.

Additionally, according to Cisco's 'Consumer Privacy Survey' CISCO (2020) carried out in 2020, almost half of the consumers (48%) feel like they do not have control over their data. Misuse or abuse of personal data is the top reason consumers lose trust in a company.

This study proposes a methodology, created under the FranchetAI project FranchetAI (2022), to develop a solution that promotes sustainable and personalised travel behaviours while preserving data privacy and user trustworthiness. FranchetAI (2022) built the methodology on top of the following pillars: (i) state-of-the-art mechanisms to safeguard data collected from smartphones by not sharing private/sensitive data with any cloud service; (ii) compliance with European best practices in usability, accessibility and explainable AI to clarify in an understandable way how the data is being processed and how the results are achieved, and, finally, (iii) building up the experience on gamification and habit changing to promote incentives (rewards, vouchers, among others) to encourage the community to opt for sustainable trip choices as well as to create more awareness amongst them.

Based on this methodology, the final solution creates awareness of the saved emissions with periodic "Carbon digest" reports (daily and weekly) via a mobile app that showcases the individual environmental impact of their transportation decisions and recommends sustainable alternatives that produce fewer or no emissions, based on the available transit options in a city.

Leveraging Explainable AI tools, plus usable and accessible interfaces, the methodology follows a user-centric approach to make data understandable by the different stakeholders (commuters, municipalities, transportation operators) after being processed by Artificial Intelligence models that understand different mobility options and their environmental impact.

For instance, the Machine Learning (ML) model that predicts the user modal choice takes into account standard sensors from smartphone devices (GPS/GNSS, accelerometer, etc.) and comes (off-the-shelf) trained to identify different types of transportation (car, bicycle, walking, etc.). To identify if a user is taking a specific bus or train route (or to recommend one afterwards), the solution requires data on the public transit network in GTFS format GTFS (2022) to train its AI models on the routes and schedules. From there, a different model responsible for GHG emissions estimates the users' carbon footprint.The solution then engages commuters to take greener options via gamification mechanisms (by comparing individual reports with the averages of local and European communities, as well as with the necessary targets to stop climate change), but especially with rewards/incentives via local challenges promoted and funded by NGOs, decision-makers and businesses willing to invest in carbon abatement. By promoting these sustainable travel behaviours and changing commuters' habits, this methodology aims to contribute to CO2 emissions reduction directly.

2. Methodology and main contributions

In order to offer an encompassing solution, we split our methodology into two different objectives: the AI approach and the GHG approach. First, to automatically understand the user's mobility patterns, we resort to artificial intelligence mechanisms, namely Federated Learning (AI approach). Secondly, after the first stage that defines the type of transportation chosen by the user, we need to infer its carbon footprint (GHG approach).

With this, in the first step, we explain the need to use machine learning algorithms on top of mobility data as well as how we can focus on the privacy of the users' data while highlighting important information from it. Moreover, we also acknowledge the need of having prior information about several aspects of the method of transportation for a correct measure of GHG emissions. Figure 1 exhibits the pipeline of the proposed methodology.

2.1. AI Approach

Following the large deluge of data, Machine Learning became the de facto solution to leverage large quantities of data and extract insights from it. Nonetheless, new regulations (e.g., GDPR) impose new approaches to the analysis of data that may contain sensitive information. Also, Federated Learning (FL) has been emerging when focusing on

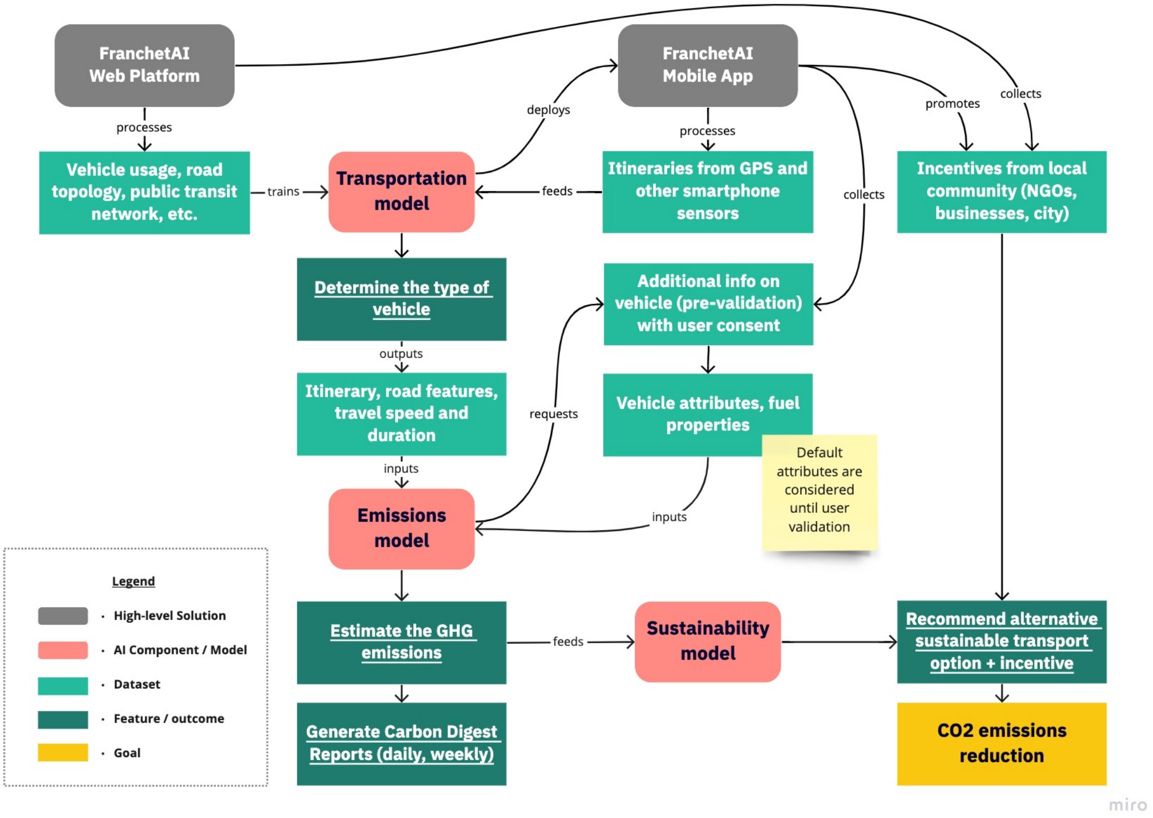

FranchetAI Web Platform
processes
Vehicle usage, road topology, public transit network, etc.
trains
Transportation model
deploys
FranchetAI Mobile App
processes
Itineraries from GPS and other smartphone sensors
feeds
collects
promotes
collects
Incentives from local community (NGOs, businesses, city)
Determine the type of vehicle
outputs
Itinerary, road features, travel speed and duration
inputs
Emissions model
requests
Additional info on vehicle (pre-validation) with user consent
Vehicle attributes, fuel properties
Default attributes are considered until user validation
inputs
Estimate the GHG emissions
feeds
Sustainability model
Recommend alternative sustainable transport option + incentive
CO2 emissions reduction
Generate Carbon Digest Reports (daily, weekly)
Legend
High-level Solution
AI Component / Model
Dataset
Feature / outcome
Goal
miro

Fig. 1: The pipeline of the proposed methodology.

not independent and identically distributed (Non-IID) data Bonawitz et. al (2019); Li et. al (2020). Such data is commonly generated on edge, local and mobile devices.

In brief, FL is a type of distributed machine learning where the data never leaves the data source. Sensitive data from different users can be leveraged to train a privacy-preserving model. In this setting, a centralized server has the initial trained model M_i and broadcasts M_i to every user. This trained machine learning model is a collection of parameters and hyperparameters which are calculated based on the training data. Typically, M_i is trained on previously collected data, open-sourced or private data. On the user side, the user device trains the model on the user's data. At each iteration, the centralized server asks N users for their new model parameters and calculates the average of all the obtained parameters. Each user can define if it will participate in the round or not, similarly, the centralized server can decline the parameters broadcasted from the decentralized users. At the end of this cycle, the server broadcasts the new parameters to every user, updating their local model Bonawitz et. al (2019); Li et. al (2020). Also, one of the goals of FL is to preserve data privacy. To do so, FL resorts to differential privacy, adding an amount of noise to the user's data, guaranteeing that individual data cannot be disclosed Wei et. al (2021). So, our AI approach is decoupled into two stages. First, we define the datasets to locally train our chosen models and our deep learning architectures, and then we define the chosen framework for developing our federated system.

For such a development, we chose the GeoLife GPS Trajectories dataset Zheng et. al (2011). It comprises GPS trajectory data from 178 users with latitude, longitude and altitude, containing a total of 17,621 trajectories. With this data, we define which data we need the users to collect. Then, by working with such data, we define the velocity, acceleration and distance of the trajectory as the main features to be calculated and used as the input of our models. Moreover, such a dataset encompasses several modes of transportation, we focused on fewer transportation modes, e.g., car, motorcycle, bike, bus or foot, to improve the accuracy of the models. This leads to the model more accurately labelling the transportation mode used by each individual user.

For the initial models, we used the Random Forest and Decision Trees resorting to the library SciKit-Learn SciKit-Learn (2021). Then, after the use of common machine learning models, other algorithms, with emphasis on deep learning, were used. This was due to the federated learning system (further explained below). These models were built based on the assumption that the initial data will be loaded as CSVs and a time-series database. To this end, the models were built with dense layers and long-short term layers. The use of these architectures is supported by the literature for similar use cases.

To offer the proposed encompassing solution, we focus our efforts on the use of state-of-the-art frameworks. In the first stage, we tested our solution on top of PySyft Ryffel et. al (2018); Ziller et. al (2021). However, due to the launch of its new version, it was important to understand the changes and how they would influence the following development. After a first evaluation, it was possible to understand the lack of support from the new version to mobile settings. As such, there was a need to evaluate other similar solutions, namely Flower Beutel et. al (2020); Flower (2022), and Tensorflow Lite Tensorflow (2022). While developing the first deep learning models, Tensorflow Tensorflow (2022) was the chosen framework, as such, both federated systems were valid alternatives. Nonetheless, even though the integration with the mobile APP still occurs, resorting to the compilation abilities of Tensorflow Lite, Flower provides integration with several machine learning frameworks. This solution allows training federated algorithms not only on mobile settings. As such, after this first stage, it was possible to define seamlessly a federated system for other models and use cases that focus on sensitive data, e.g., data obtained from each municipality or city. Flower also provides several averaging algorithms which comprise differential privacy alternatives. This main feature improves the privacy-preserving goal of the solution, also improving its trustworthiness. With this in mind, Figure 2 represents the overall layout of the federated system.

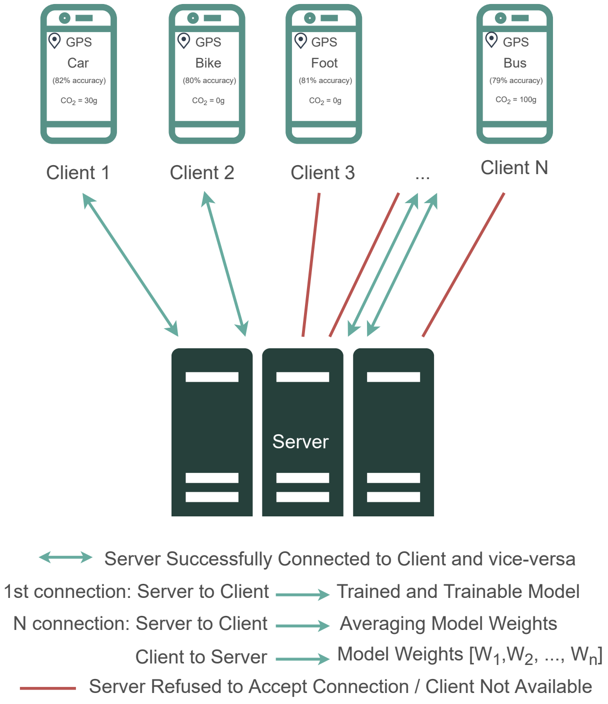

GPS
Car
(82% accuracy)
CO₂ = 30g
GPS
Bike
(80% accuracy)
CO₂ = 0g
GPS
Foot
(81% accuracy)
CO₂ = 0g
GPS
Bus
(79% accuracy)
CO₂ = 100g
Client 1
Client 2
Client 3
...
Client N
Server
Server Successfully Connected to Client and vice-versa
1st connection: Server to Client → Trained and Trainable Model
N connection: Server to Client → Averaging Model Weights
Client to Server → Model Weights [W1,W2, ..., Wn]
Server Refused to Accept Connection / Client Not Available

Fig. 2: Representation of the proposed federated system and representative visualization of the output.

Moreover, we acknowledge the need to employ Explainable AI tools to let users understand how their data is being used. To do so, we apply the SHAP framework[1]. Such framework allows to visually explain which data is being used for the training of the models. Since we limit the number of labels and data used for this training, this explainability allows the users to understand which features impact the outcome/output of the model.

2.2. GHG Approach

The methodology adopted for estimating Greenhouse Gases (GHG) and air pollution emissions and measuring their reduction is based on the "tank-to-wheel" Life-Cycle Assessment (LCA), thus, by only considering the operation of the vehicle. The emissions are estimated based on the CORe INventory AIR emissions (CORINAIR) system, i.e. the method approved by the European Environment Agency (EEA) to assess emissions. CORINAIR adheres to the IPCC IPCC (2006) guidelines, used globally by environmental protection agencies for national and regional evaluations. According to the IPCC Guidelines IPCC (2006) for greenhouse gasses, a compiler builds a decision tree in order to select the appropriate methodology, with different complexities and data requirements. Therefore, we apply the Tier 3 methodology from EMEP/EEA EMEP/EEA (2019) (formerly called the EMEP CORINAIR emission inventory guidebook) by considering equation 1. Moreover, the GHG estimations are based on the ultimate CO2 emissions, which are a result of different processes (combustion of fuel; combustion of lubricant oil; and addition of carbon-containing additives in the exhaust).

$$E_{ik} = e_{ik}(v) \cdot a_k, \tag{1}$$

where E_{ik} is the exhaust emissions of pollutant i induced by a vehicle technology k (in grammes); e_{ik} is the emission factor as a function of the vehicle driving speed (in grammes per kilometre); a_k is the transport activity in vehicle kilometres travelled (VKT) for vehicle technology k. The emissions are calculated individually for each client of the FranchetAI Mobile App by considering the average driving speed of the road links that constitute an individual trip. The previous AI approach described provides information on traffic data (modal choice, trip route and distance and driving speed) necessary to calculate clients' emissions resulting from traffic activity. Also, information on vehicle technology is required, i.e. the eurostandard information which is accessed by taking into account the age of the vehicle. Therefore, a user is asked to give this detailed information, otherwise, a default technology is used (*Euro 4*).

3. Results and Discussion

3.1. AI Approach

The focus of the first tests with the GeoLife dataset helped limit and create general labels for the transportation modes. We partitioned the initial dataset into test and train datasets, 30% and 70% respectively. The first 70% of the dataset was used to train the model, while the remaining 30% was used to test it. Also, while limiting the used labels, we were able to diminish the tree length and improve the results of Random Forests and Decision Trees by around 5%, reaching an accuracy of 81% in less than 3 minutes of training. Moreover, the developed Deep Learning models, based on dense and long-short term memory layers, have yet to achieve similar accuracy results, nonetheless, the results are similar to the previous ones, currently reaching an accuracy of 75% with a training run time of 5 minutes. Focusing on the current tests based on the proposed federated system, we followed a similar definition of the dataset. We further sharded the test dataset into 10 shards to test the system with 10 clients. Such initial results were promising, showing that the trained model is able to label the remaining trajectories with similar accuracy and each individual user, with 1/10 of the dataset, is able to train a new local model and share its parameters with the centralized server.

[1] https://github.com/slundberg/shap

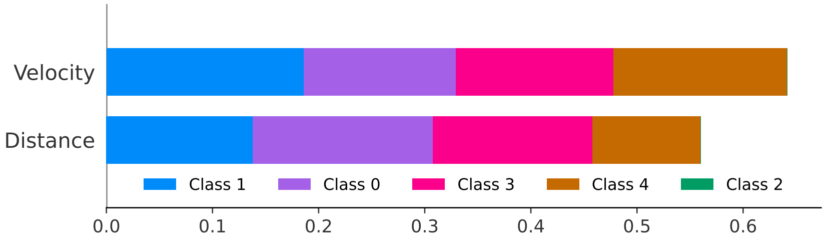
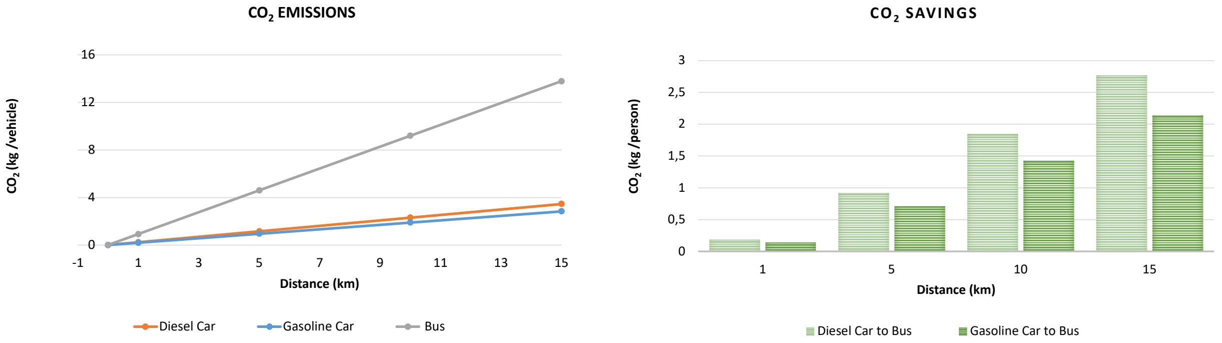


Fig. 3: Example of the current explainability outcome.

The explainability feature allows to understand the weight giving to each feature to label each class (Figure 3). With classes(e.g., car, foot, bus) being the output of the model. The mean velocity and the distance of each trajectory are the features of the model.

3.2. Example GHG Approach

The emissions model currently proposed needs the following information: i) the mean velocity of the trajectory; ii) the type of fuel of the car; iii) the category of the vehicle (i.e., Passenger, Bus, Heavy Duty and, Motorcycle); iv) the total distance of the trip; v) the year of the vehicle. The velocity and the total distance of the trajectory are direct elements of the calculation of such emissions as well as the type of vehicle and its category. The year and category are further used for the definition of the Euro Standard. When such information is not disclosed by the user, the GHG emissions are estimated based on Euro 4 and the category of the vehicle is defined by the previously trained AI models.



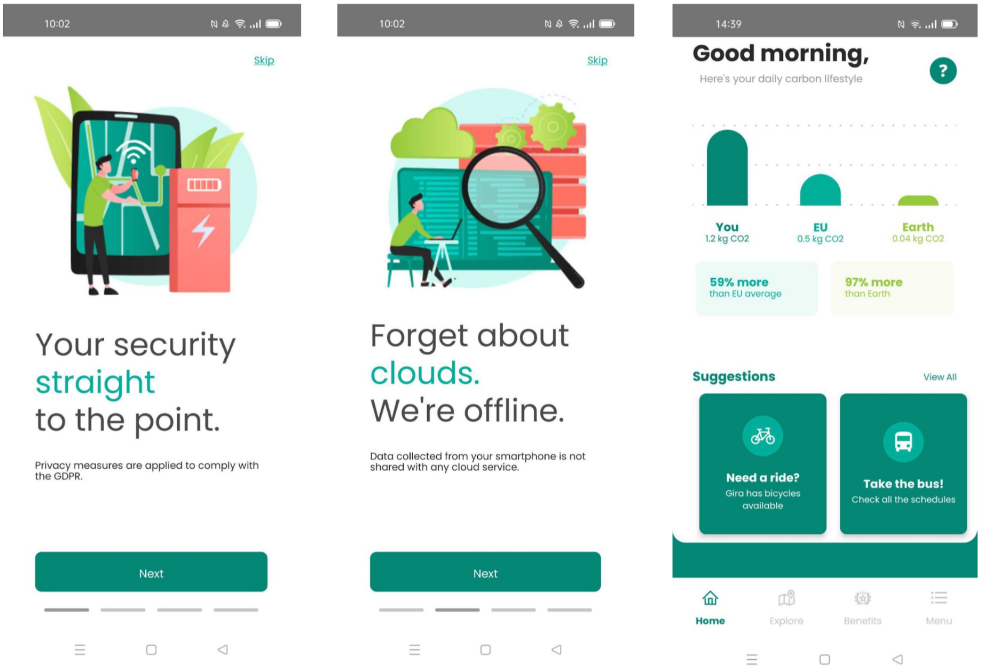
(a) CO_2 emissions of an user commuting with a diesel car, gasoline car and a bus. (b) CO_2 savings of an user commuting with a diesel car, gasoline car and a bus.

Fig. 4: Example of the proposed solution for *GHG* emissions.

Figure 4 presents an example of the usage of our emissions model. For instance, for a user that has been commuting for 30 min at 30km/h, one may analyse the CO2 induced by different vehicle modes (diesel/gasoline car or bus) in kilograms per vehicle. Also, by assuming that an urban bus will have an occupancy of 20 people, the impact of using such a more environmentally friendly vehicle is presented.

3.3. FranchetAI Mobile Prototype

FranchetAI app (see Figure 5) is inspired by the Cotoneaster franchetii, a super plant acknowledged for filtering 20% more emissions (namely automobile air pollutants) than other shrubs. This is a digital rewarding mechanism for people opting for sustainable mobility options (public transit, electric vehicles, and other light modes) ensuring transparency and trustworthiness between the user and the different stakeholders creating the incentives. Overall, the goal of such a solution is to let users understand their carbon footprint while offering travelling alternatives and rewards for travelling in a more sustainable way by changing their current habits.



Your security straight to the point.

Privacy measures are applied to comply with the GDPR.

Forget about clouds. We're offline.

Data collected from your smartphone is not shared with any cloud service.

Good morning,

Here's your daily carbon lifestyle

59% more than EU average

97% more than Earth

Need a ride? Gira has bicycles available

Take the bus! Check all the schedules

Fig. 5: FranchetAI Mobile App.

Hence, data is collected from a smartphone only with the user's consent and it is not shared with any cloud service. In order to improve the models that classify the transportation modes and the emissions, a few attributes and parameters are sent to our server to retrain them. These do not reflect the user's location or any other personal data that might have been shared with our application, being specific to the model parameters. Besides, FranchetAI helps in increasing the users' awareness of their transport environment impact choices, also, it gives them rewards when a "good behaviour" is made which might be provided by local stores and services. Therefore, FranchetAI plays a key role in achieving the SDGs regarding climate change and also help build cities' economies while promoting local businesses.

4. Conclusion

This methodology leverages best practices for differentiating on privacy and engaging citizens. Specifically, it uses AI/ML models to classify personas based on user feedback collected in the mobile app and provide recommendations on routing options that produce fewer/no emissions. Also, the solution uses AI/ML models to detect the transportation modes based on user content and data-sharing consent and to understand the impact and quality of incentives. The users have full control of their data, explicitly knowing which of its data is used for locally inferring the system's models and which is used for training new models in a secure and privacy-preserving manner. Following a federated learning setting and security protocols, sensitive data must not leave, at any given moment, the users' premises. Regarding future work to be performed, the methodology will be validated within real-world scenarios. Data from past and ongoing initiatives (namely other R&D projects) is being used as well as open data and third-party platforms to ensure the solution is as off-the-shelf as possible (although local context and data will help personalize it to the target communities). Also, we want to evaluate different strategies for the federated system and understand the impact of adding differential privacy to real-world use cases.

Acknowledgements

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