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D2.6 Conceptual Model and Reference Architecture V1

(Version 1.3, 10/11/2022)

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Abbreviations

| | |
|----------|---|
| EC | European Commission |
| EU | European Union |
| CSV | Comma Separated Values |
| GA | Grant Agreement |
| H2020 | Horizon 2020 Program of the European Commission |
| WP | Work Package |
| CRISP-DM | Cross-Industry Standard Process for Data Mining |
| BDV | Big Data Value |
| BDVA | Big Data Value Association |
| RA | Reference Architecture |
| VPME | Virtualized Policy Management Environment |
| EOSC | European Open Science Cloud |
| KDD | Knowledge Discovery in Databases |
| XAI | eXplainable AI |
| ML | Machine Learning |
| DL | Deep Learning |
| NLP | Natural Language Processing |
| HPC | Cloud and High Performance Computing |
| ETL | Extract, Transform, and Load |
| XML | eXtensible Markup Language |

| | |
|------------------------|---|
| DB | DataBase |
| CSV | Comma Separated Values |
| NER | Named-Entity Recognition |
| IaaS | Infrastructure-as-a-Service |
| PaaS | Platform-as-a-Service |
| IdP | Identity Provider |
| VO | Virtual Organisation |
| SSH | Secure Shell Protocol |
| SHAP | SHapley Additive exPlanations |
| TOSCA | Topology and Orchestration Specification for Cloud Applications |
| IM | Instant Messaging |
| AWS | Amazon Web Services |
| Infrastructure Manager | |
| OIDC | OpenID Connect |
| VM | Virtual Machine |

Executive summary

AI4PublicPolicy is a joint effort of policy makers and Cloud/AI experts to unveil AI's potential for automated, transparent and citizen-centric development of public policies. To this end, the project will deliver, validate, demonstrate and promote a novel Open Cloud platform (i.e. AI4PublicPolicy platform) for automated, scalable, transparent and citizen-centric policy management based on unique AI technologies.

AI4PublicPolicy will provide public authorities, public administrators and other policy making stakeholders with a complete environment for AI-based policy making. Policy makers will be able to design, develop, deploy, validate and fine-tune data-driven, evidence-based policies from a single-entry point.

The AI4PublicPolicy Policy Making Process leverages on the CRISP-DM methodology to address the following objectives:

- Provide a data-driven, AI-based and evidence-based approach
- Promote and facilitate the collaboration between Policy Makers and AI Experts
- Involve citizens and other stakeholders in the Policy evaluation and optimization
- Boost the acceptance of the policies presenting and explaining the Policy development outcomes
- Reuse and share the Policy development models and Datasets across different domains and countries

The AI4PublicPolicy Reference Architecture takes into account and addresses the following concerns of the BDV Reference Model:

- Data Analytics.
- Data Protection
- Data Processing Architectures
- Data management
- Cloud and High Performance Computing
- Data sharing platforms
- Cybersecurity and Trust

The components of the AI4PublicPolicy RA are divided into three main subsystems or pillars:

- Reusable and Interoperable Dataset
 - Dataset Collection and Management
 - Semantic Interoperability
 - Cross Country Interoperability
 - Datasets and Policies Catalogue
- Policy Transparency and Trust
 - Explainable AI (XAI)
 - Policy Explainability and Interpretation
 - AI Security
 - AutoML
- Policy Extraction and Evaluation
 - Text and Sentiment Analysis

- Policy Extraction
- Policy Evaluation and Optimization
- VPME

The AI4PublicPolicy platform is built on top of the multi-layered EOSC Compute Platform. Its main layers are:

- The **Federated Resource Providers** layer
- The **Compute and Data Federation** layer
- The **Platforms** layer
- The vertical **Service Management Tools** layer

The components and the whole Reference Architecture has been validated towards both the Conceptual Model, describing how the components interacts to fulfil the AI-based Policy Making Process in the main high-level scenarios, and the Pilots user stories reported in deliverable D2.1, mapping the components to the needs of each user story.

1 Introduction

1.1 The AI4PublicPolicy Project

AI4PublicPolicy is a joint effort of policy makers and Cloud/AI experts to unveil AI's potential for automated, transparent and citizen-centric development of public policies. To this end, the project will deliver, validate, demonstrate and promote a novel Open Cloud platform (i.e. AI4PublicPolicy platform) for automated, scalable, transparent and citizen-centric policy management based on unique AI technologies. The AI4PublicPolicy platform will be an Open Virtualized Policy Management Environment (VPME) that will provide fully-fledged policy development/management functionalities based on AI technologies such as Machine Learning (ML), Deep Learning (DL), NLP and chatbots, while leveraging citizens' participation and feedback. It will support the entire policy development lifecycle, based on technologies for the extraction, simulation, evaluation and optimization of interoperable and reusable public policies, with emphasis on citizen-centric policies development and optimization through the realization of citizen-oriented feedback loops. AI4PublicPolicy will complement public policy development functionalities with the ever-important process reengineering and organization transformation activities towards ensuring the effective transition from legacy policy development models to emerging AI-based policy making.

The AI4PublicPolicy VPME will be integrated with EOSC with a dual objective. First to facilitate access to the Cloud and HPC resources of EOSC/EGI that are required to enable the project's AI tools, second to boost the sustainability and wider use of the project's developments. AI4PublicPolicy's business plan for sustaining, expanding and commercializing the AI tools and the VPME is based on the development of a community of interested and engaged stakeholders (i.e., public authorities and other policy makers) around the project's platform.

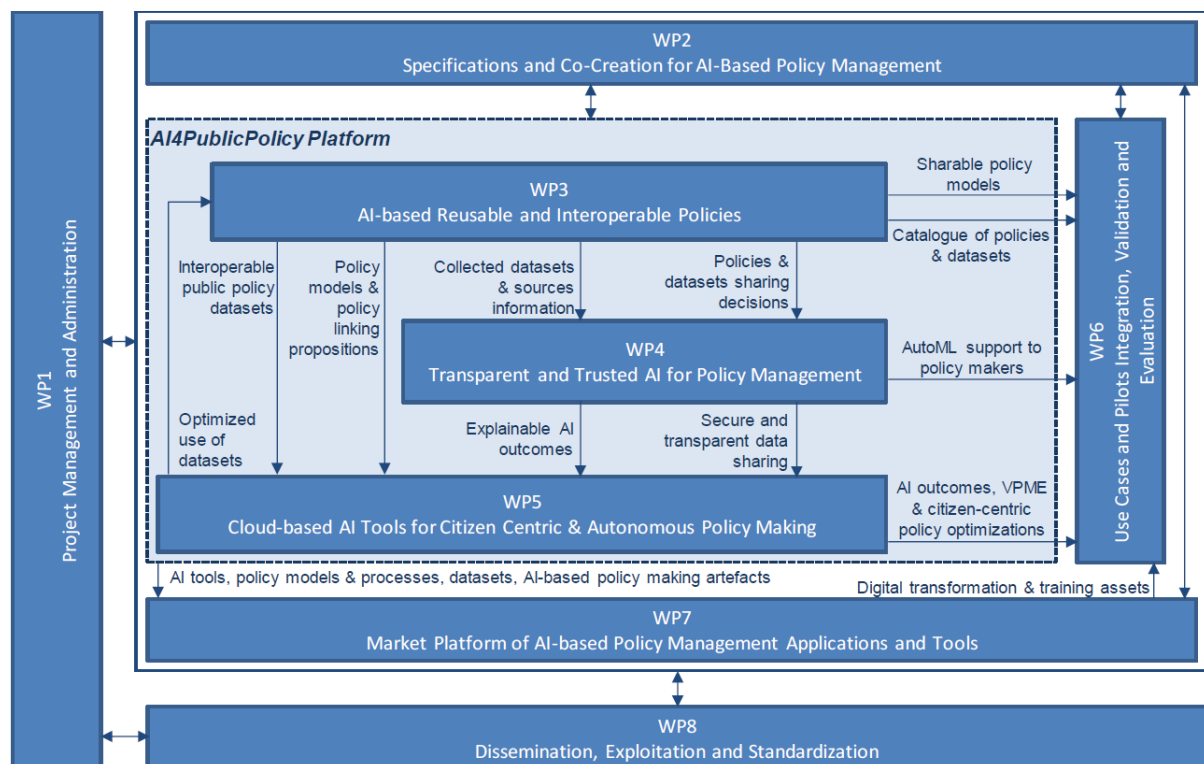


Figure 1. AI4PublicPolicy methodological approach

1.2 Description of WP2

Work package 2 (WP2) is a central technical work package in the AI4PublicPolicy project. Work package 2 is divided in a set of tasks of major tasks: definethe definition of the AI4PublicPolicy architecture (task T2.5), identify the technical requirements, review standards and regulations (task

T2.2), analyze the policy making process (task 2.6) and identify data models of the data sets to be utilized in AI4PublicPolicy.

The objectives of WP2 are to:

- Specify the overall architecture for the AI4PublicPolicy platform by identifying components, their functionalities and interconnection, ensuring their coherency with the requirements and global architecture.
- Identify and track end user and technical requirements provided by the use case partners and the technical contributors of AI4PublicPolicy.
- Review the standards and regulations and identify appropriate ones that need to be monitored and followed in the project.
- Analyse the policy making processes to ensure that the outcomes of the project address and enhance/improve these processes, while reducing the bottlenecks in public administration and ensuring high quality and adoption of results.
- Define the data models of the datasets to be utilized for the development, training and actual utilization of the AI models and algorithms of AI4PublicPolicy.
- Define the co-creation. Relevant activities will be regularly reported in D2.8, in-line with the description of the deliverable.

1.3 Purpose and scope of the document

This deliverable addresses the first of the WP2 objectives reported above, presenting the Conceptual Model for AI-based Policy Making and the Reference Architecture for the AI4PublicPolicy platform.

1.4 Structure of the document

This document is comprised of the following chapters:

- The **first chapter** of the document presents an introduction to the project and the document.
- The **second chapter** of the document presents the Conceptual Model for AI-based Policy Making
- The **third chapter** of the document presents the Reference Architecture for the AI4PublicPolicy platform
- The **fourth chapter** of the document presents the result of the validation of the RA towards the user stories provided for the different pilots
- The **fifth chapter** of the document describes the main scenarios of the AI-based Policy Making

Finally, the document includes a sixth chapter with the conclusions of the document

2 Conceptual Model

AI4PublicPolicy VPME aims to provide public authorities, public administrators and other policy making stakeholders with a complete environment for AI-based policy making, as shown later in Figure 2. Policy makers will be able to design, develop, deploy, validate and fine-tune data-driven, evidence-based policies from a single-entry point.

As a starting point they will provide data and policy information to the VPME. Accordingly, they will be able to use the AI tools in order to extract data-driven insights (e.g., Policy Recommendations, Policy Simulations). At the same time, they will be supported by AutoML techniques, while they will also have the opportunity of executing the XAI tools towards easing the interpretation and presentation of the policies to relevant stakeholders.

The project's policy development approach will be local actors' centric: local actors (citizens, businesses and other actors) will be actively engaged in the development, validation and evaluation of the policies and their feedbacks, obtained through public channels and interfaces (e.g. social media for implicit feedback, surveys, applications of local authorities for explicit feedback), will be analysed and taken into account in the development of the policies, as well as in their optimization.

As shown in Figure 2, the VPME will also enable policy makers to repurpose and reuse policy models and datasets in different policy development contexts and applications. This will be boosted by the fact that the VPME will centralize access to all the different policy models and datasets through the EOSC portal/marketplace.

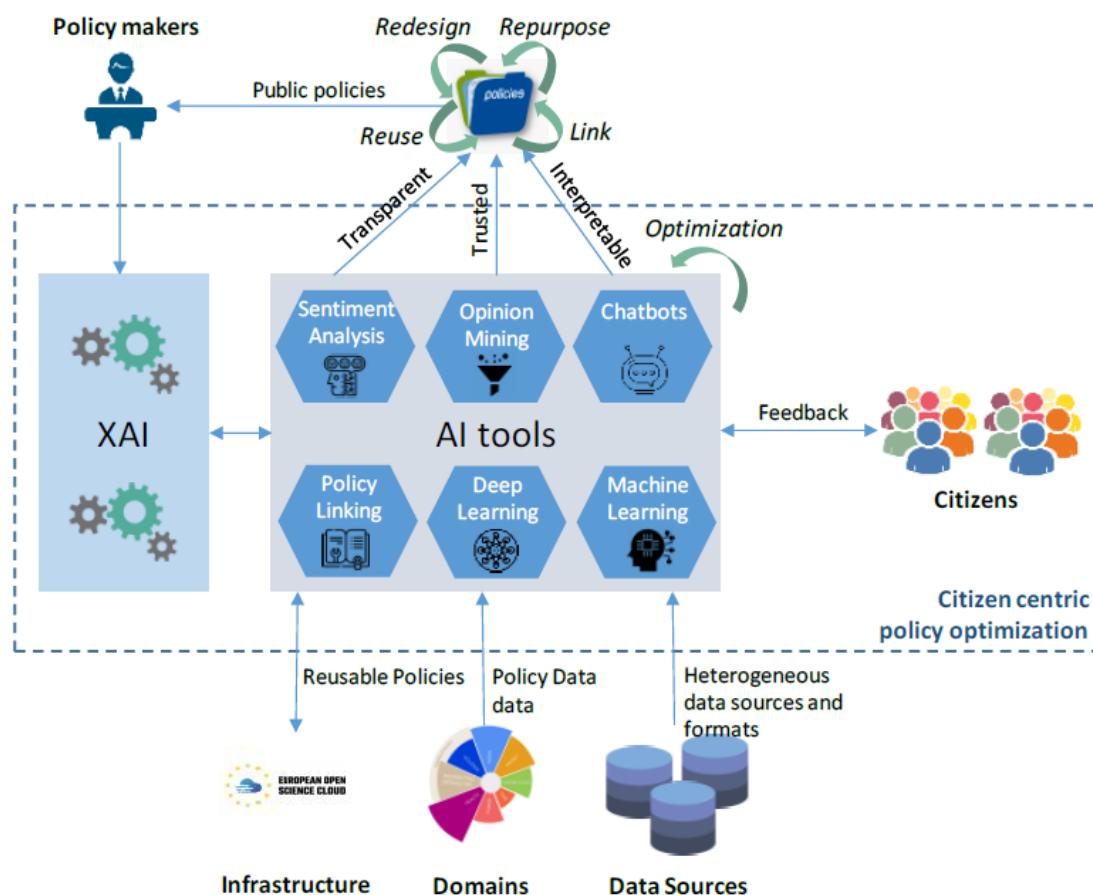


Figure 2. AI4PublicPolicy Conceptual Model

2.1 CRISP-DM Methodology

In 2000, as response to common issues and needs, an industry-driven methodology called Cross-Industry Standard Process for Data Mining (CRISP-DM) was introduced as an alternative to

Knowledge Discovery in Databases (KDD), a previous data mining methodology [CRISP-DM]. It also consolidated the original KDD model and its various extensions. The iterative executions of CRISP-DM stand as the most distinguishing feature compared to initial KDD that assumes a sequential execution of its steps. CRISP-DM, much like KDD, aims at providing practitioners with guidelines to perform data mining on large datasets.

The main steps of CRISP-DM, as depicted in Figure 3 below are as follows:

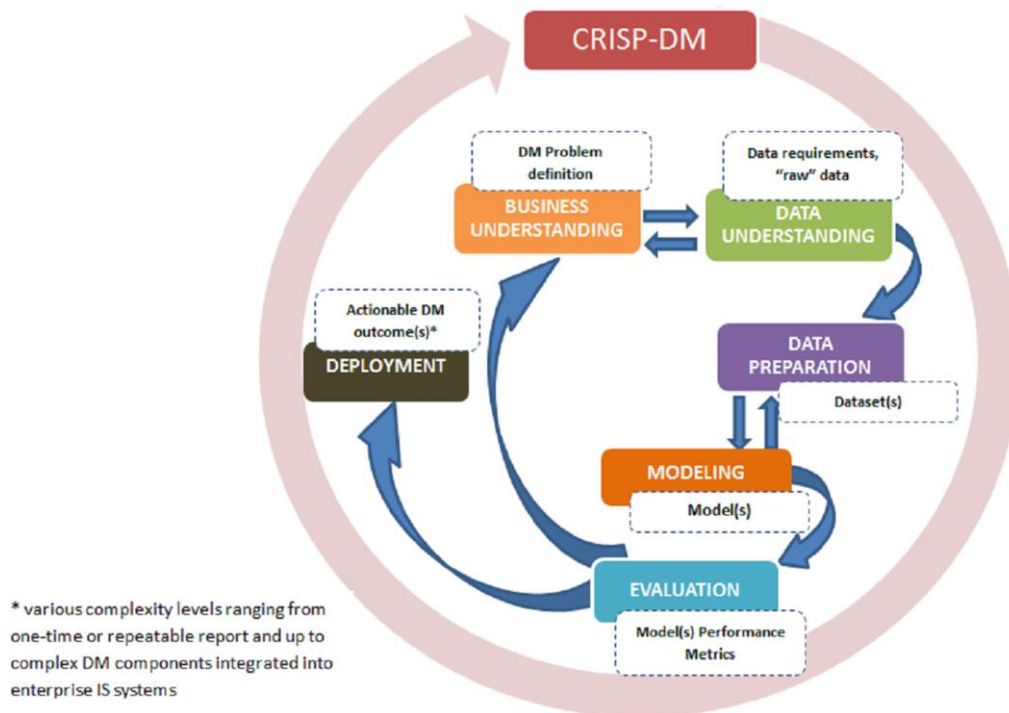


Figure 3. CRISP-DM Methodology

- Phase 1: Business understanding: The focus of the first step is to gain an understanding of the project objectives and requirements from a business perspective followed by converting these into data mining problem definitions. Presentation of a preliminary plan to achieve the objectives are also included in this first step.
- Phase 2: Data understanding: This step begins with an initial data collection and proceeds with activities in order to get familiar with the data, identify data quality issues, discover first insights into the data, and potentially detect and form hypotheses.
- Phase 3: Data preparation: The third step covers activities required to construct the final dataset from the initial raw data. Data preparation tasks are performed repeatedly.
- Phase 4: Modelling phase: In this step, various modelling techniques are selected and applied followed by calibrating their parameters. Typically, several techniques are used for the same data mining problem.
- Phase 5: Evaluation of the model(s): The fifth step begins with the quality perspective and then, before proceeding to final model deployment, ascertains that the model(s) achieves the business objectives. At the end of this phase, a decision should be reached on how to use data mining results.
- Phase 6: Deployment phase: In the final step, the models are deployed to enable end-customers to use the data as basis for decisions, or support in the business process. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized, presented, distributed in a way that the end-user can use it. Depending on the requirements, the deployment phase can be as simple as generating a report or as complex as implementing a repeatable data mining process.

2.2 Policy Making Process

The AI4PublicPolicy Policy Making Process leverages on the CRISP-DM methodology to address the following objectives:

- Provide a data-driven, AI-based and evidence-based approach
- Promote and facilitate the collaboration between Policy Makers and AI Experts
- Involve citizens and other stakeholders in the Policy evaluation and optimization
- Boost the acceptance of the policies presenting and explaining the Policy development outcomes
- Reuse and share the Policy development models and Datasets

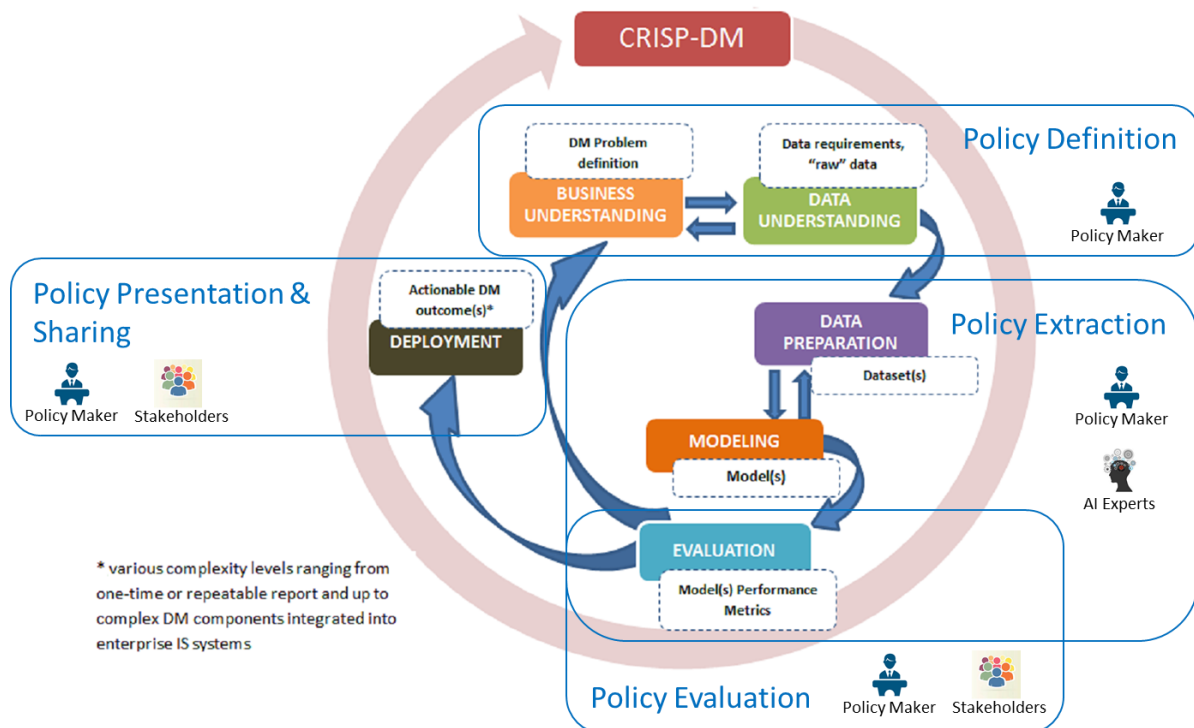


Figure 4. AI4PublicPolicy Policy making Process

The main steps of the Policy Making Process, as depicted in Figure 4 above are as follows:

- **Phase 1 - Policy Definition:** In this step the Policy Maker starts creating an Analytical Policy Model describing the Policy problem(s) and associating and describing relevant Datasets for the Policy.
- **Phase 2 - Policy Extraction:** In this step an AI Expert, or the Policy Maker himself with AutoML support, creates one or more AI Workflows to analyse the datasets and prepare the data to train and test AI Models based on different AI Algorithms, in order to provide responses (insight, recommendations) to the Policy problem(s). The Policy Maker executes the AI Models on new data, analyses the responses and validates the AI Models.
- **Phase 3 - Policy Evaluation:** In this step the Policy Maker involves the relevant stakeholders (citizens, business and other local actors) in the Policy Evaluation creating one or more surveys on the Policy problems, AI model responses and Policy alternatives. The Policy Maker then evaluates the stakeholders feedbacks, presented with a statistical or sentiment scoring, and decides to complete the Policy with actionable outcomes or optimizing it taking into account the stakeholders feedbacks.

- **Phase 4 - Policy Presentation and Sharing:** In this step the Policy Maker uses XAI techniques provided by the platform to better understand and explain the rationales under the AI Models responses. Once completed this step the Policy Maker could present the final Analytical Policy Model, which represent the result of the AI-based Policy Making Process, to the relevant stakeholders and publish it in the shared catalogue

3 Reference Architecture

3.1 BDV Reference Model

AI4PublicPolicy main focus is on collecting and analyzing data for making public policy. The BDV reference model was defined by the BDVA and is a framework to locate data related technologies [BDVA]. The reference model is structured into different horizontal and vertical concerns represented in Figure 5. The horizontal concerns represent core components of the data value chain, while horizontal concerns represent cross-cutting issues that may affect all the horizontal concerns. The horizontal concerns, although represented as a stack, are independent layers.

The *data visualization* and user interaction layer deals with the tools for representing big data and the interaction between users and the visualization of the big data.

Data analytics deals with the techniques for understanding and extracting knowledge from data. These include machine learning, deep learning, natural language processing, event and pattern discovery, deep learning technologies, and high performance data analytics that take advantage of high performance computing.

Data processing architectures must deal with data at rest (stored data) and data in motion (streams of data) coming from heterogeneous resources in different formats (structured, non-structured). The data processing architectures must be designed so that they can take advantage of high performance computing and cloud computing in order to scale to the increasing amount of data being produced.

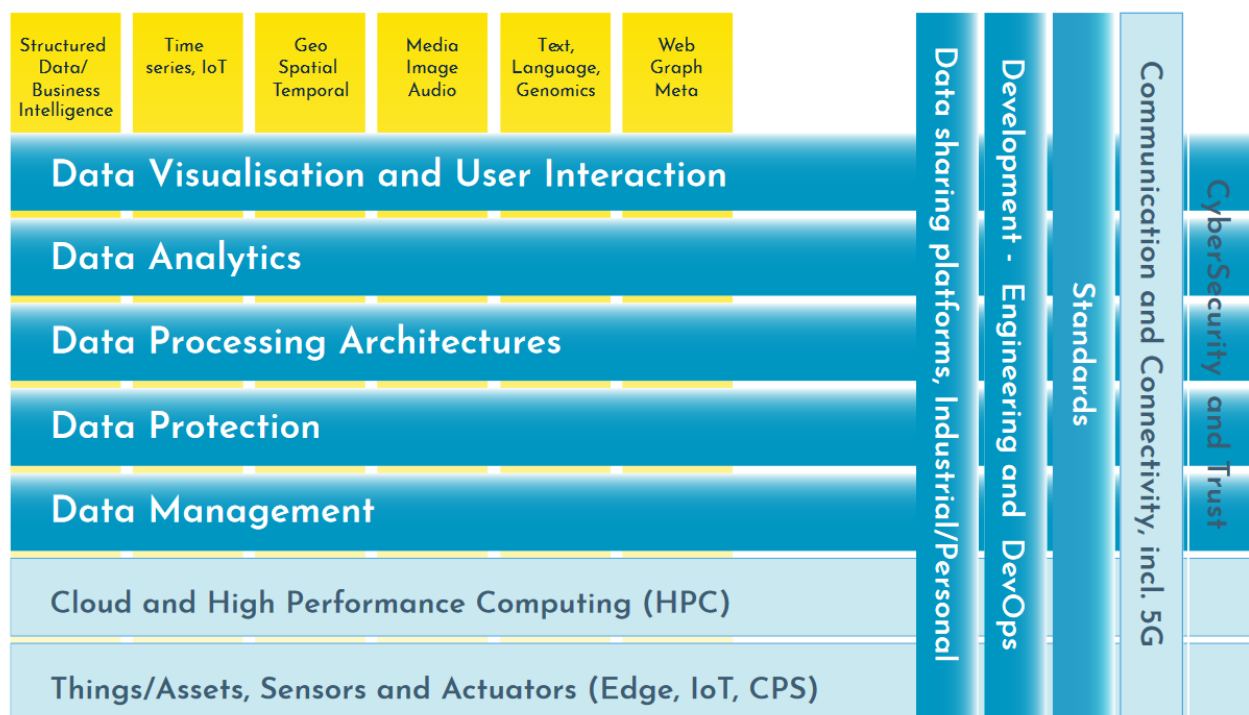


Figure 5. BDVA Reference Model

Data protection deals with the techniques to protect person-specific and sensitive data. Privacy protection includes protecting analytics applications and the (cloud) underlying infrastructure from data leakages. These mechanisms must ensure anonymity and protection against reversibility.

Data management deals with the techniques for dealing with large amounts of data that are being produced. Multilingualism of data sources, especially relevant in EU, makes difficult to analyse the data since they are in different languages. The lack of a common representation of the data creates silos of data that cannot be processed without a semantic interoperability layer.

Cloud and High Performance Computing (HPC) are basic pillars for effective data processing and management. The use of cloud for data processing is a standard nowadays. All cloud platforms provide different infrastructures for storing and analyzing data. The use of HPC resources has been recognized as a complementary approach for extreme data analytics. The European Open Science Cloud (EOSC) is a federated system based on a set of existing research infrastructures which delivers a catalogue of services, software and data from major research infrastructures.

Among the vertical aspects it is worth mentioning the market places for sharing data and facilitating the usage of horizontal aspects.

3.2 Relation between BDV Reference Model and AI4PublicPolicy

AI4PublicPolicy aims at delivering an Open Virtualized Policy Management Environment for automated, transparent and citizen centric development of public policies. For that purpose AI4PublicPolicy will collect, process and analyze large volumes of datasets from different data sources (e.g., citizens, public authorities databases, social media...) using AI technologies and cloud computing resources. AI4PublicPolicy will integrate technologies for semantic interoperability of different data policy data sources, leveraging existing ontologies for policy description. AI4PublicPolicy will be integrated with EOSC that will ensure that public authorities have access to cloud and HPC resources.

More specifically, AI4PublicPolicy addresses the following concerns of the BDV Reference Model:

- *Data Analytics.* AI4PublicPolicy will use AI tools for policy modelling, extraction, simulation and recommendation. The AI tools to be used in AI4PublicPolicy include machine learning to extract policy related knowledge from large datasets, opinion mining and sentiment analysis based on the opinions of citizens expressed in social media.
- *Data Protection.* AI4PublicPolicy will use anonymized data.
- *Data Processing Architectures.* AI4PublicPolicy will deal with data-at-rest or stored data coming from policy authorities and the interaction of citizens with the administration and the services they provide. The AI4PublicPolicy architecture will also deal with streaming data coming from citizens' opinions on social media. So the architecture must integrate both kinds of data management and analytics tools.
- *Data management.* AI4PublicPolicy will deal with structured data (data in tables) and unstructured data (opinions in natural language). AI4PublicPolicy will use natural language processing tools for avoiding the creation of policy data silos in different languages. AI4PublicPolicy development is guided by five pilots from different European countries with different languages. The project will integrate tools for semantic interoperability of policy data sources.
- *Cloud and High Performance Computing.* AI4PublicPolicy will be integrated with the EOSC portal to facilitate access to cloud and HPC resources.
- *Data sharing platforms.* AI4PublicPolicy integration with EOSC portal will deliver a complete environment for AI-based policy making which will enable to share datasets, policies and the AI4PublicPolicy Virtual Policy Management Environment (VPME).
- *Cybersecurity and Trust.* AI4PublicPolicy will provide *eXplainable AI (XAI)* which will allow to make explicit the rationale behind the policy recommendations and which data were driving the decisions. AI4PublicPolicy will deliver defence strategies against poisoning attacks of data that may have an impact on the learned models.

3.3 AI4PublicPolicy Components

The definition of the software architecture is derived from the requirements of the use cases defined by the pilots in deliverable D2.1 Use Case Scenarios Definition and Design. Figure 6 presents the main components of AI4PublicPolicy. These components are logically grouped into three main modules that represent three technical work packages of the project according to the DoA that is,

Reusable and Interoperable Policies (WP3), Transparent and Trusted AI for Policy Management (WP4) and AI Tools for Autonomous Policy Making (WP5). All these components are independent components that provide REST interfaces. The architecture notation is derived from the UML notation using lollipop notation for the interfaces. The *half circle* indicates the user of an interface provided by the *ball*.

The target users of the AI4PublicPolicy platform are policy makers and data scientists. The entry point of AI4PublicPolicy for both types of users is the VPME, which is a web application that acts as the user interface (UI) and acts as front-end for all the functionalities of the AI4PublicPolicy platform. Depending on the type of user (policy maker, data scientist), the VPME will present different functionality; for instance, the data scientist may define analytical workflows while the policy maker which is not aware of the different ML techniques may use autoML features.

There are external data sources such as social media (e.g., Twitter interface) or other forums from which data for opinion mining and sentiment analysis is collected.

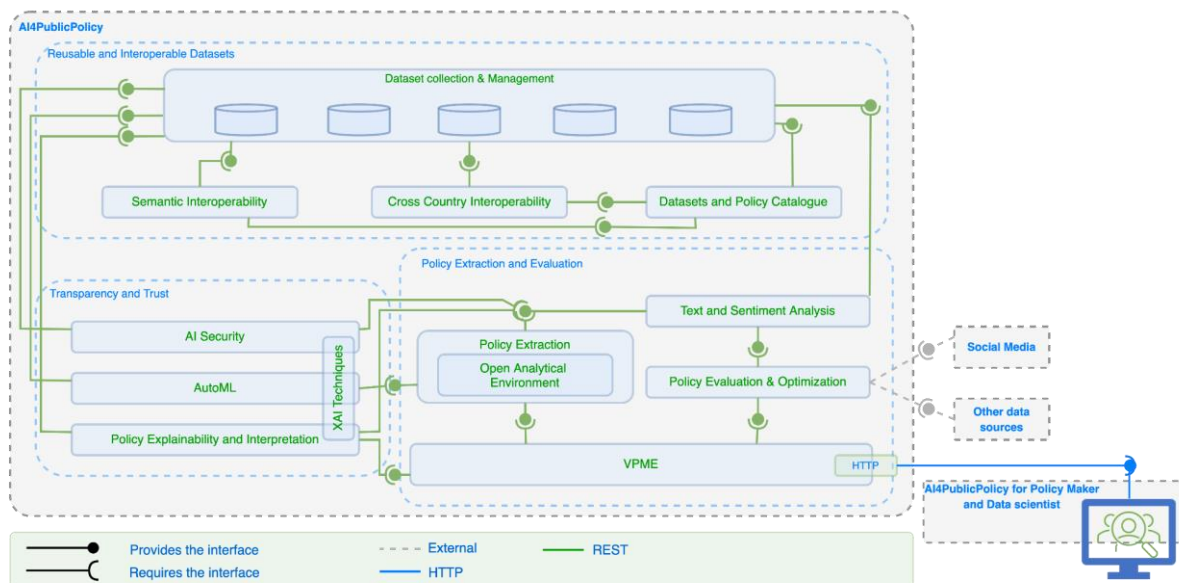


Figure 6. AI4PublicPolicy Architecture Components

The following sections describe in detail the components of the architecture of AI4PublicPolicy providing. The functionality of each component is described detailing the subcomponents, its inputs and outputs.

3.3.1 Dataset Collection and Management

Component Description

The goal of this task is to provide the software tools needed to collect and manage the datasets that will produce the pilots in the project. This tool should be generic enough so that it can be used for collecting other datasets. The datasets will be stored to be later analyzed or make them available for others in case of data that can be made public. The software should be generic enough so that it can be used with different datasets and data formats. Another requirement of the component is that it should be able to collect data-at-rest (e.g., from CSV files) or data-at-movement (e.g., streaming data from sensors).

The collection of datasets will be done through a web service (RESt API) that datasets providers will connect to for providing information on the location of the dataset to be loaded into AI4PublicPolicy platform. Figure 7 shows the subcomponents of the Data Collection and Management component. The *Data Retrieval* component will connect to that endpoint, and then, it will download the data and invoke the *Data Injector* which will store the data in a *Data Store*. The main component in the data

collection process (the *data injector*) will be implemented using *Apache Beam*¹, an open source framework for defining data pipelines. *Beam* can be used for the Extract, Transform, and Load (ETL) process. These tasks are useful for moving data between different storage media and data sources, transforming data into a more desirable format, or loading data onto a new system. *Beam* meets the requirements regarding different data formats and the nature of data (at-rest and data streaming). *Beam* is a generic tool that must be instantiated with a *runner* that is the actual component executing the pipeline. *Beam* is integrated with *Flink*, *Samza*, and *Spark*, among other systems that can be used as runners. *Beam* supports several programming languages such as Java and Python. *Beam* can read data in different formats: text, Avro, XML, ... It can connect to message systems (e.g., RabbitMq, Kafka ...) and databases (e.g., HBase, Cassandra, BigTable...). The *Beam* pipeline stores the read data in a datastore whose schema must be previously defined. The dataset schema to be loaded must match the schema of one of the tables in the datastore. The data collection component will check that there is a table that matches that schema.

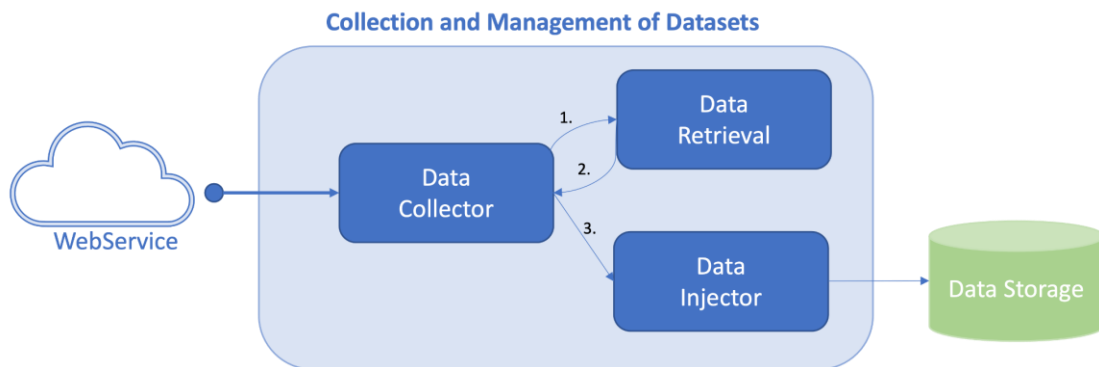


Figure 7. Dataset Collection and Management subcomponents

Input

Data set format

Endpoint for the input dataset

Datastore endpoint

Output

Data in a AI4PublicPolicy datastore

Sequence Diagram

The next sequence diagram, Figure 8, shows the invocations triggered to the different subcomponents when a request to collect data is received by the Dataset Collection and Management component.

¹ <https://beam.apache.org/>

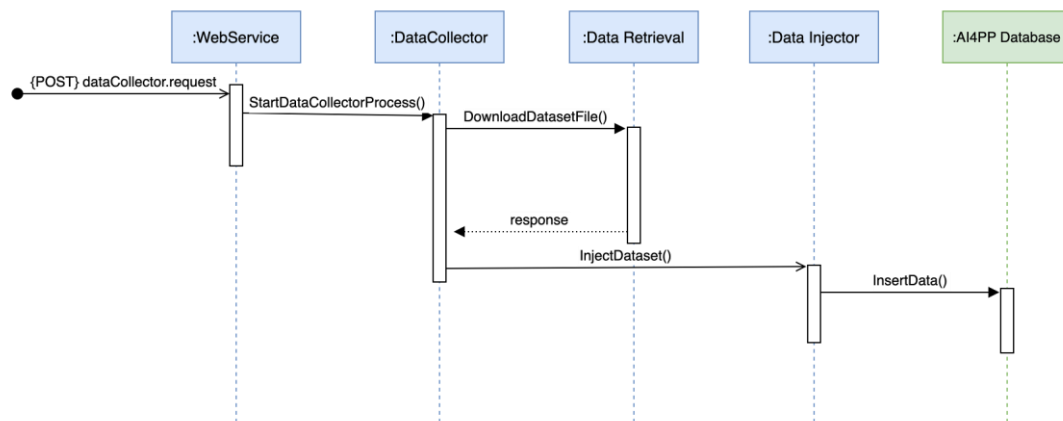


Figure 8. Data Collection Process

3.3.2 Semantic Interoperability

Component Description

The goal of the Semantic Interoperability toolkit is to dynamically enable interoperability. It aids datasets on becoming interoperable without the user changes, by acting as an interoperability mediator. Realising interoperability is a key challenge due to the existence of multiple ontologies and archetypes for policy making [Xue22], that need to semantically interoperate.

The semantic interoperability toolkit will be based on the Plug'n'Interoperate solution [Malo13], by exploiting the same basic principle of Plug'n'Play / self-configuration as to automate as much as possible, the configuration and participation of systems into the Interoperability environment. The solution is made possible by the existence of 'interoperability drivers' which define translations in between data formats, and that are taken by an interoperability support system to enable fully interoperability of systems in the data exchange environment. In the Plug'n'Interoperate environment, systems simply plug (into the interoperability support system) and promptly interoperate with other systems present in the data-sharing environment.

Like PnI, the semantic interoperability toolkit will provide interoperability enabling methods, in order to ensure interoperability between Public Policy datasets. The interoperability toolkit allows datasets from different pilots to be made interoperable in a seamless manner.

The semantic interoperability toolkit will be based on Interoperability specifications, which is an Interoperability Artefact without the capability to execute interoperations by itself. An interoperability artefact specifies all the actions that must be executed to perform the information transfer between two data formats: (i) the information source; and (ii) the target data source.

An Interoperability specification describes how to perform the interoperation between a source data format and a target data format. The realisation of that description is only possible if the concepts represented in each data format are well understood and a matching between the concepts of these data formats can be performed.

The semantic interoperability toolkit will provide the necessary interoperability specifications in order to enable the mapping between the different data formats available within AI4PublicPolicy.

Input

The semantic interoperability toolkit will receive as input some datasets in a specific data format, and a request for a target data format. With these, the toolkit will execute the necessary interoperability specification to convert the source to target data format.

Output

The semantic interoperability toolkit will provide the dataset in the target data format.

Sequence Diagram

Figure 9 presents interactions of the semantic interoperability toolkit with other components for processing requests.

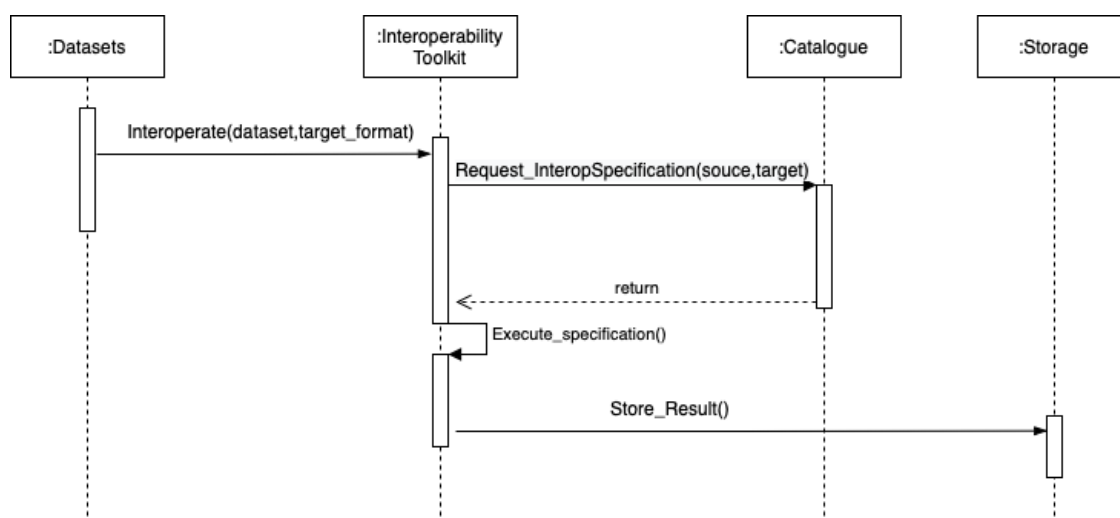


Figure 9. Semantics Interoperability interaction with other components

3.3.3 Cross Country Interoperability

Component Description

This component will translate data from one language to another target language in order to share data and policies in order to increase the sharing of data and policies across Europe. Datasets and policies originate in different countries and are defined in the language of the origin country; this diminishes the chances of data and polices being reused, compared or applied in different countries. Assuming that the datasets and policies are in English is a strong assumption that most of the time does not hold. This component will receive data in text format in a given language and the target language and produce the same information in the destination language. This component will be implemented using available translation services such as Google translate, which can be integrated with spreadsheets for translating data in tabular form.

Input

Text to be translated, language of the text and destination language.

Output

Text in the target language

Sequence Diagrams

This component will take data from a text file, the original language and the target language and invoke the translation service. Figure 10 shows the interactions of this component with other components

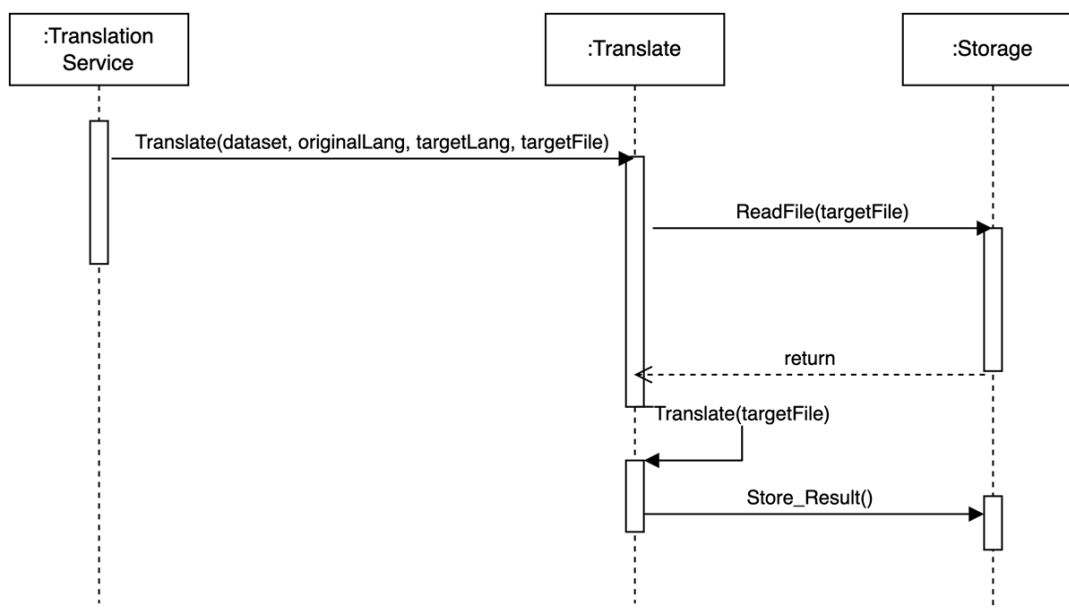


Figure 10. Cross Country Interoperability integration with other components

3.3.4 Datasets and Policies Catalogue

Component Description

The Catalogue for Policies & Datasets is a component which will list all Policies and Datasets related to AI4PublicPolices. All information interesting for the execution of the project will be hosted in a searchable catalogue, which can be of use for users that are in need of information related to policies and datasets for specific situations.

This searchable catalogue of policies and datasets is in the form of a registry. Through this catalogue, access to policies and data will be democratised by making them available for analysis, usage and implementation in various domains. Through the provision of such a registry, the AI tools to analyze data will be only ever a click away, which will lead to the reduction of the time it takes for public administrators to create policies on the registered data. The catalogue will enable easy access and increased searchability to the stakeholders, by providing an adaptable search engine that will offer semantic AI models that will create semantic links among the different keywords, for identifying the semantic fingerprint of the searched policy or dataset and providing in real-time the requested result.

Apart from the increased searchability, the catalogue will provide more knowledge base functionalities for comparison and recommendation of datasets and/or policies. By modelling datasets and policies, along with associated metadata, the catalogue can offer some decision support system functionalities, such as recommendation of related datasets or policies. This can be accomplished using a “similarity rank”, and when a user accesses a specific entry in the catalogue, it will also receive information about related datasets and/or policies.

Input

This component needs as input information about the dataset or policy that should be listed, and then it will retrieve and show the information about the specific dataset and the related datasets.

Output

This component provides a searchable catalogue with capabilities to show the information about policies and datasets, but also decision support tools capabilities by providing information about related datasets or policies.

Sequence Diagram

Figure 11 shows the interaction of the Catalogue with other components when the catalogue is browsed.

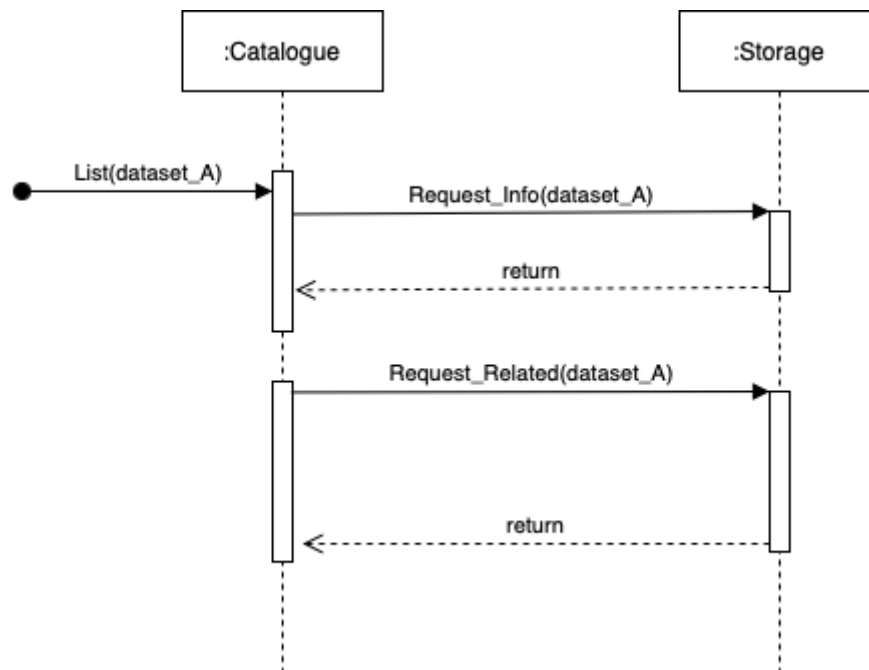


Figure 11. Catalogue interaction with other components

3.3.5 XAI Techniques

Component Description

This component is in charge of providing information for analysing and explaining the predictions made by machine learning models. regarding the rationale behind a recommendation. The XAI component gets a model (classifier, regression or decision trees) and generates a dashboard for checking the model performance and SHAP values, which rely on input perturbations to explain the model output. The dashboard will present a set of interactive aspects the user can control. Examples of plots to be shown are: model performance, SHAP dependence plot, impact of a feature on a predicted value, SHAP interaction, features importance... A set of default dashboards for each model will be developed as well as customised dashboards for the project pilots. The software initially considered to implement this component is ExplainerDashboard², which can be integrated with Jupyter notebooks that will be used by the front end of the AI4PublicPolicy, the VPME. An example of the dashboard is given in Figure 12. On the left contribution of each feature to predict the sales of tickets. On the right side, the precision of a different prediction is shown (real vs predicted values).

² <https://explainerdashboard.readthedocs.io>

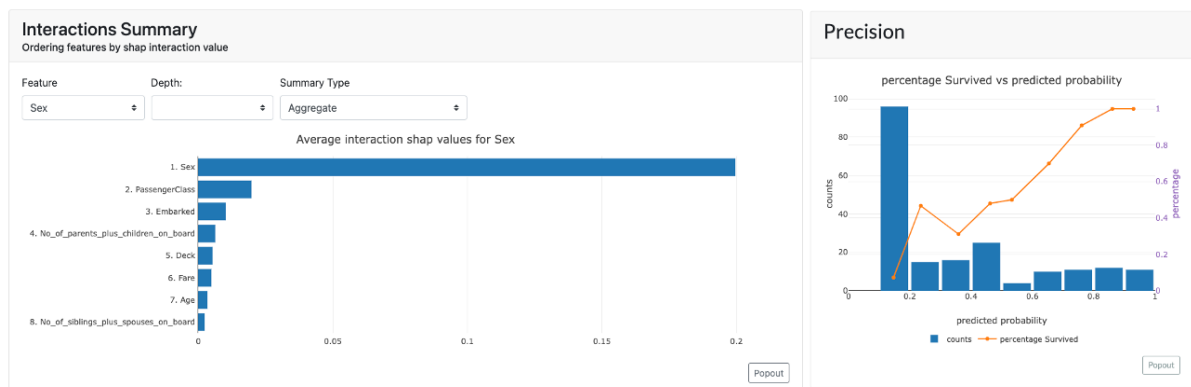


Figure 12. XAI Dashboard example

Input

The predefined dashboards receive the type of model (classifier, regression, decision tree), the model and a dataset

Output

The XAI component will produce an interactive dashboard integrated with Jupyter notebooks.

Sequence Diagram

Figure 13 shows the EXplainable AI flow.

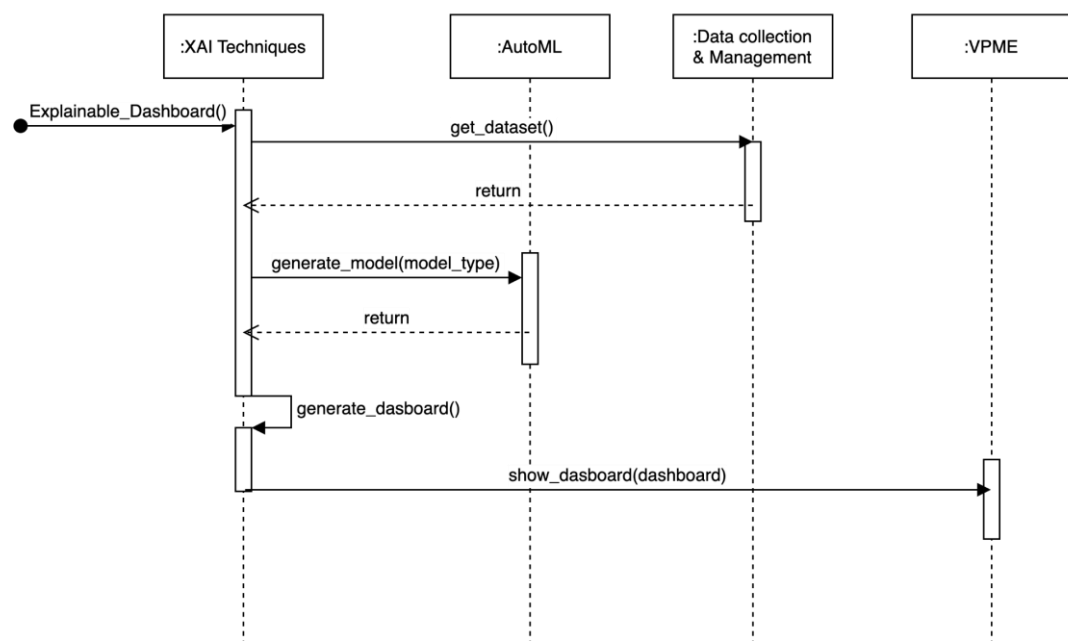


Figure 13. EXplainable AI Techniques interaction with other components

3.3.6 Policy Explainability and Interpretation

Component Description

This component will realise the tools to build the policy models which will produce the analysis and interpretation of the policy datasets given by the project's pilots (Athens, Lisbon, Nicosia, Genova and Burgas). The policy models will produce insights drawn from the datasets and forecasts on each unique scenario presented below. The policy maker will be able to understand the patterns existed in data and the models forecasts in order to fine-tune or shape future policies

- **Athens Pilot:**

- Analysis of incidents reported in various regions and better allocation of teams based on optimization techniques in order to resolve them (additional data may be required).
- Parking spaces visualisation
 - Forecasts for the available parking spaces in a near future window for each parking zone available in the dataset.

- **Genova Pilot:**

- Implementation of a tool which will allow policy makers:
 - Run what-if scenarios to optimise the average (or maximum) distance required of senior citizens to reach their nearest polling location
 - The variable polling locations will form the set of decision variables for the policy maker to see how their use can impact the quality of life of senior citizens during elections.

- **Lisbon Pilot:**

- Combination of the data given in order to create a sustainability index.
 - The sustainability index will be implemented based on generally known sustainability targets/standards.
- The results can be either given in a textual format or can be visualised in a map depicting the city's regions.

- **Burgas Pilot:**

- Implementation of a tool which will be able to measure pipes RUL (Remaining Useful Life)
- Forecast the amount of water used in each household.

- **Nicosia Pilot:**

- Analysis of bus routes & occupancy, parking usage and citizens preferences in order to propose the best alternative for the citizen in relation to travel time and travel costs.
- Analyse bus routes, parking spaces revenues and environmental performance (CO2 emissions, fuel consumption) in order to improve environmental performance and management for the city.
- Produce inclusiveness zones for disabled people based on the bus routes and environmental performance (CO2 emissions, fuel consumption) datasets.

The different scenarios described for each pilot are created upon the inspection of available datasets. A transformation can take place to them after the finalisation of the use cases from the provided user stories.

Among the technologies which will be used for the implementation of the tools will be Machine Learning and Deep Learning algorithms (e.g., clustering algorithms, QARMA (INTRASOFT's ML algorithm), Artificial Neural Networks etc.) through Keras and Tensorflow libraries. The optimization technologies which will probably be used are widely known solvers such as Gurobi, SCIP and OR-Tools.

Input

Datasets which are described in deliverables D1.10 and D2.3

Output

The component will have as output the policy models build upon the input datasets. These models will perform analysis on the data and will produce a variety of visualisations and in addition forecasts that can be used for the policy maker in order to reshape or create a variety of policies. Indicative examples of policies that can be drawn from each scenario are:

- **Athens Pilot**

Based on the forecasts for the available parking spaces a policy can be made in order to raise or lessen the parking prices so as to increase the municipality's profit or to enhance the parking space availability.

- **Genova Pilot**

Based on the optimal polling locations suggestion policy model a policy maker can alter the polling buildings for the citizen convenience.

- **Lisbon Pilot**

Through creating and visualising a sustainability index a policy maker will be able to have a clear view of the city's areas index and maybe he will be able to produce policies in order to enhance the sustainability index of areas that have small index scores.

- **Burgas Pilot**

The policy model will be able to forecast a pipe's RUL or in which points a pipe may have leakage. From these forecasts a policy can be drawn in order to proactively fix or replace these pipes.

- **Nicosia Pilot**

Through the analysis of the bus routes, parking spaces revenues and occupancy and the environmental performance it will be possible to build visualisations which will help explain hidden insights from the data and build ML models and optimization algorithms that will be able to predict/output the best way to travel from a point A to B, the most environment friendly one and cost effective. Furthermore, it will be attempted to develop better city services for the disabled people and enhance their quality of life.

3.3.7 AI Security

Component Description

The objective of this task is to deliver defence strategies against AI threats that will attempt to sabotage AI models in ways that compromise their correct operation. In particular, the mechanisms should primarily protect the AI systems against data poisoning and evasion attacks.

Starting with the data poisoning attacks, in the data collected from our data sources, an attacker can potentially inject designated adversarial samples into training data to affect the resulting decision function. Hence, ensuring the purity of training data and improving the robustness of learning algorithms are two main countermeasures towards such adversaries at the training phase.

In this case the Cyber-Defence tool has to check the data received from the various data sources and possibly detect any anomalies in the samples. Here different strategies are available as a detection based on data provenance strategy and the XAI techniques.

The second defence is a revisited adversarial training technique, which trains empirically robust models using Fast Gradient Sign method for the adversarial training and has significantly lower cost respect to the projected gradient descent-based training. In general, at this point the defence tool should train the model using new inputs with adversarial perturbations and correct output labels aiming at minimising the errors caused by adversarial data.

Figure 14 below shows a high level architecture of the defensive process.

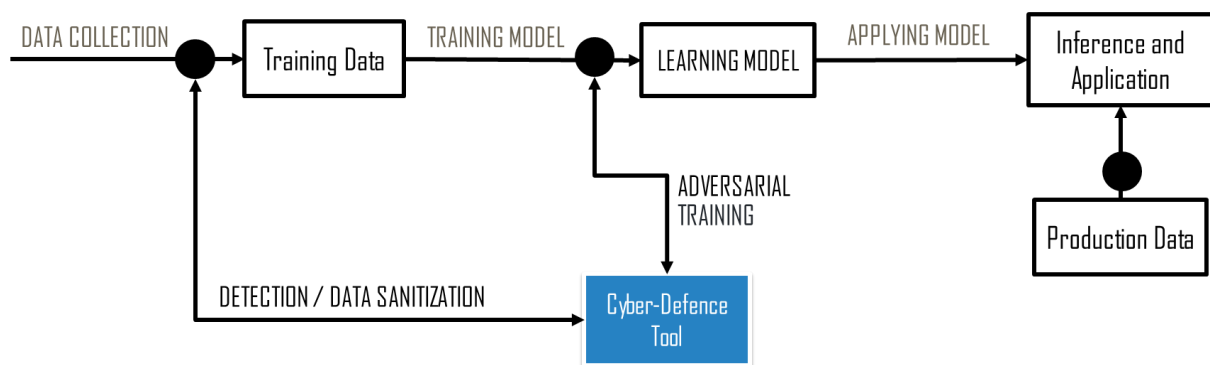


Figure 14. AI Security defensive process architecture

Input

Poisoning Detector:

- data collected from the pilot sources

Evasion Training:

- policy model

Output

Poisoning Detector:

- sanitized training data

Evasion Training:

- robust policy model

3.3.8 AutoML

Component Description

This is a component for selecting among a set of well-established algorithms the optimum algorithms to realize the AI processes chain. The mechanism realizing the latter will automatically extract statistical meta-features from datasets to perform an optimum mapping, while also considering all processes steps and dependencies within an analysis pipeline / chain. The are following subcomponents:

Dataset Explorer

1. User selects the datasets that will serve as an input to the AutoML tool.
2. Selects parameters of the data loading:

- Columns to load/ignore.
- Target column (the value of which should be predicted).
- Some transformation of the data (like featurization of dateTime values to separate fields (day, weekday, month)).

3. Source of the data: DB or raw CSV file.

Data Visualizer

After the data set is selected the user can preview the data in the

- Table preview
- Maybe some other graphical representation of the data

AutoML Pipeline

A subcomponent which allows the user to choose parameters of the AutoML Engine (defaults are used if nothing is selected) and start the AutoML process.

Parameters to select (specific to the AutoML engine used):

- Search algorithm,
- General timeout
- Iteration timeout
- Algorithms filter
- Early stopping (conditions)
- Number of cross validations

AutoML Engine

A component that takes datasets, parameters from the user as an input and finds the best models that fit.

Input

Datasets (managed by the Data Collection and Management component):

- DB table (cloud)
- CSV file

Output

Policy Model with the following additional details:

- Algorithm name
- Metaparameters of the model
- Accuracy
- Datasets used for training the model
- Feature importance: features are ranked based on their influence on the trained model

Extraction flow

The subcomponents and the pipeline for the AutoML component is shown in Figure 15.

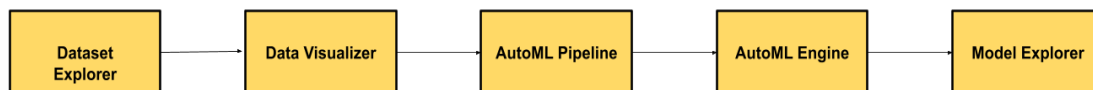


Figure 15. AutoML internal architecture

3.3.9 Text and Sentiment Analysis

Component Description

The purpose of the Text and Sentiment Analysis component is to provide the sentiment of citizens feedback to Municipalities. To achieve that, the sentiment of each sentence/comment is evaluated using complex Machine Learning models built, as well as robust and load-balanced data processing pipelines. Sentiment analysis models specialise in polarity (positive, negative, neutral) but also on feelings and emotions (angry, happy, sad, etc), urgency (urgent, not urgent), and even intentions (interested or not interested).

The input data is raw text format. The data is then processed using Natural Language Processing aiming at extracting the sentiment and emotion of each sentence. The resulting output is stored in an ElasticSearch index. When the ElasticSearch index is queried, results returned are aggregated therefore providing a clear visualisation around what was searched, usually in a front-end application.

Input

Raw text; data sources from the pilots (structured and unstructured) such as citizens Tweets, comments from various platforms, complaints, reports, surveys.

Output

Analysed aggregated output in JSON format. The values of the sentiment will be described as numeric representation: 0 for neutral, -1 for negative and 1 for positive.

Subcomponents

Text Analyzer

The Text Analyzer passes the raw text through an NER model to identify entities and then tokenizes them in an array and stores the resulting output in an ElasticSearch index along with the original text.

Figure 16 shows the Text Analysis flow.

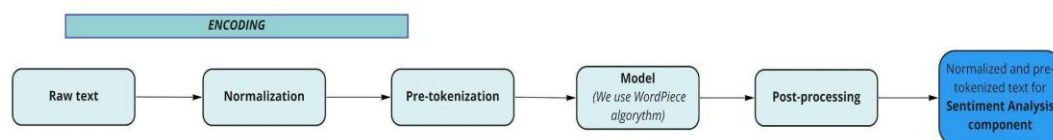


Figure 16. Text Analysis flow

Sentiment Analyzer flow, Figure 17:

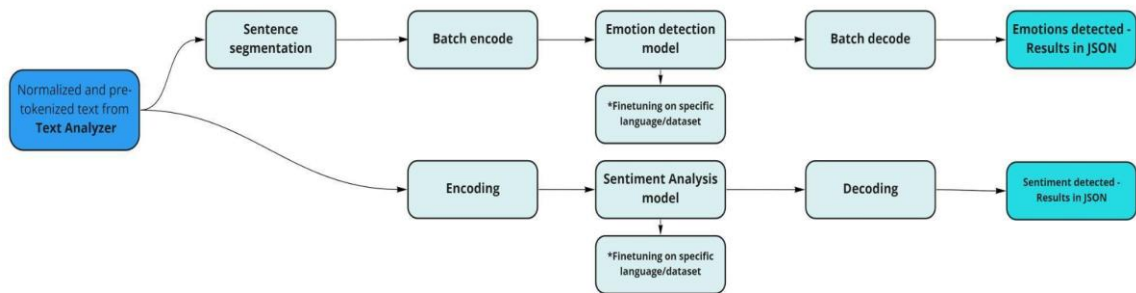


Figure 17. Sentiment Analyzer flow

3.3.10 Policy Extraction

Component Description

This toolkit provides a functionality to the policy maker to choose an AI workflow from the catalogue of ML/DL workflows (pre-built by a Data scientist) and apply it to the relevant dataset. The toolkit will return a policy model which then will be used by a policy maker to estimate parameters of the policy and ultimately to propose the policy that is based on the dataset, recommendation from the AI model and the policy maker's interpretation of the results.

Contrary to the AutoML component, the policy maker could explicitly choose different AI models and evaluate their performance on a real dataset and manually choose the one that performs best.

Subcomponents

Dataset Explorer

This subcomponent allows to visually see and edit dataset and make some basic transformation to it to prepare it for the further processing in the pipeline:

- Adjust column name
- Filter columns
- Adjust column types

AI Algorithms Catalogue

Contains all available ML/DL algorithms to choose from.

Model Explorer

1. The ML pipeline returns the list of models with the information on how well they performed.
2. User can go through models and evaluate the results:
 - Algorithm name
 - Accuracy
 - Feature importance: features are ranked based on their influence on the trained model
 - Duration
3. Save: Policy makers can save the model and load it later for further exploration.

4. Deploy: Policy makers can deploy the model so it will be available through a service endpoint to other AI4PP components.

Open Analytical Environment

It's a platform which provides basic building blocks for constructing AI pipelines. There are several options, but mainly there are two categories:

1. Code-centric: **Jupyter Notebooks**. The pipeline is built using Jupyter Notebooks and Python ML libraries, more coding is required by the data scientist.
2. Visual-centric: **KNIME**. Building ML pipelines with functional blocks that KNIME provides by connecting them in the visual designer, less coding is required.

Input

Datasets:

- Dataset
- Selected AI algorithm from the catalogue
- Parameters of the AI algorithm

Output

Policy Model with the following additional details:

- Algorithm name
- Accuracy
- Feature importance: features are ranked based on their influence on the trained model

Subcomponents

Figure 18 shows the pipeline of this component and the subcomponents.



Figure 18. Policy Extraction internal architecture

3.3.11 Policy Evaluation and Optimization

Component Description

The objective of this component is to allow the simulation and evaluation of the policies developed by making use of the opinions and feedback of local actors to propose new insights and improvements.

In particular, a new virtual environment process will be designed which: in a first phase proposes the developed policy models to local actors and through different channels (existing Pilot applications, online surveys, social media) collects the explicit and implicit feedback using the tools we provide, and in the subsequent phase these feedbacks are used as inputs to a mechanism that extracts new insights and capabilities to augment the artificial intelligence algorithms. More specifically, the tool to analyze the responses can give weights to the input features of the AI algorithm, can remove/add features based on the opinions of the actors or can give insights to the policy maker.

The tools that extract feedback from the different channels will adopt mechanisms developed for Sentiment Analysis, Opinion Mining and Text Analytics.

Using the presented procedure, we involve citizens in the policy co-creation process, while allowing the selection of the most correct data sources and policy models considering the expectations of local actors.

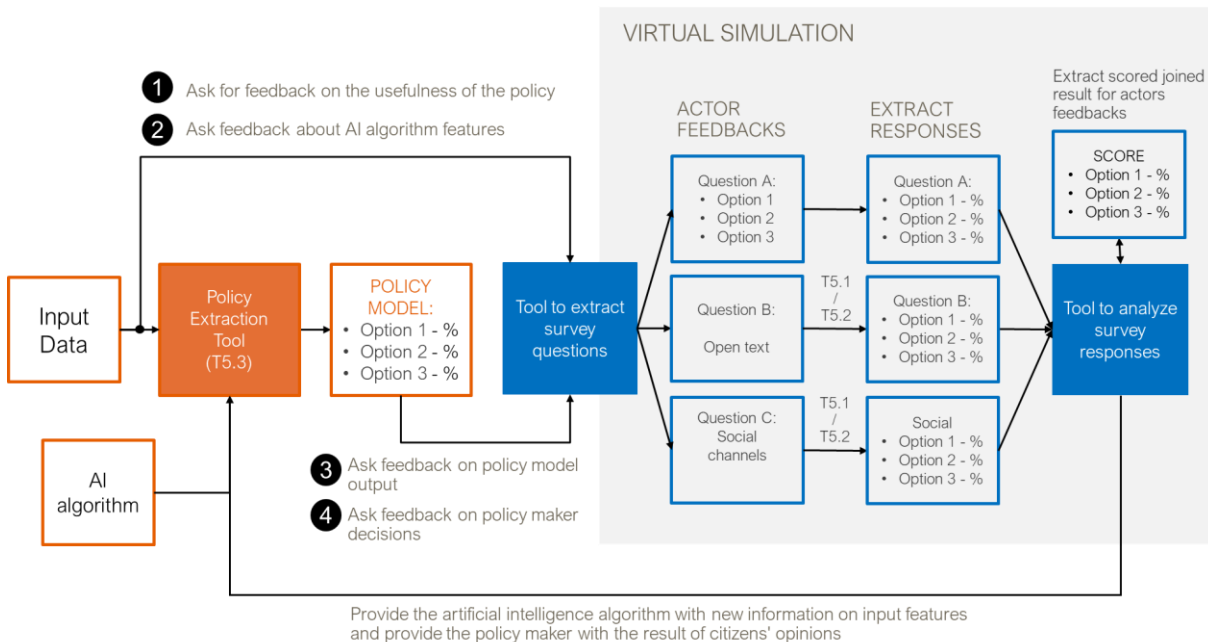


Figure 19. Policy evaluation and optimization flow

Input

Policy models as outcome of the AI algorithms and feedback collected from the local actors through different channels.

Output

- new features for AI algorithms and other insight from the responses analysis
- dataset enrichments

3.3.12 VPME

Component Description

The Virtualized Policy Management Environment (VPME) will incorporate the policy models, the explainability AI mechanisms outcomes from Explainable AI (XAI) for Policy Interpretation and the Policy Explainability and Interpretation Tools, the Sentiment Analysis and Opinion Mining and Text Analytics for Document Processing components which will create the sentiment analysis, the opinion mining and the text analytics tools respectively and finally the security interfaces. The aforementioned technology components which will be incorporated in the VPME platform will be accessed through their APIs. The VPME will be a cloud-based platform and will be realised through Jupyter Notebooks from which all the different components will be connected through the API each component will offer. Each Pilot will have a set of Jupyter Notebooks which will analyse each dataset and then the proper visualisations will be produced along with the models' forecasts. The above VPME description is also depicted in the Sequence Diagram section.

Input

Models and functionalities for AI-based reusable and interoperable policies, explainable AI (XAI) for policy interpretation, policy explainability and interpretation tools, secure operation of AI algorithms and tools, AutoML for public administrators, sentiment analysis and Opinion Mining and Text Analytics for Document Processing along with the Policy-Related Datasets.

Output

A Cloud based platform based on a set of Jupyter Notebooks through which the user will be able to control the models and functionalities created by the different set of tools.

Subcomponents

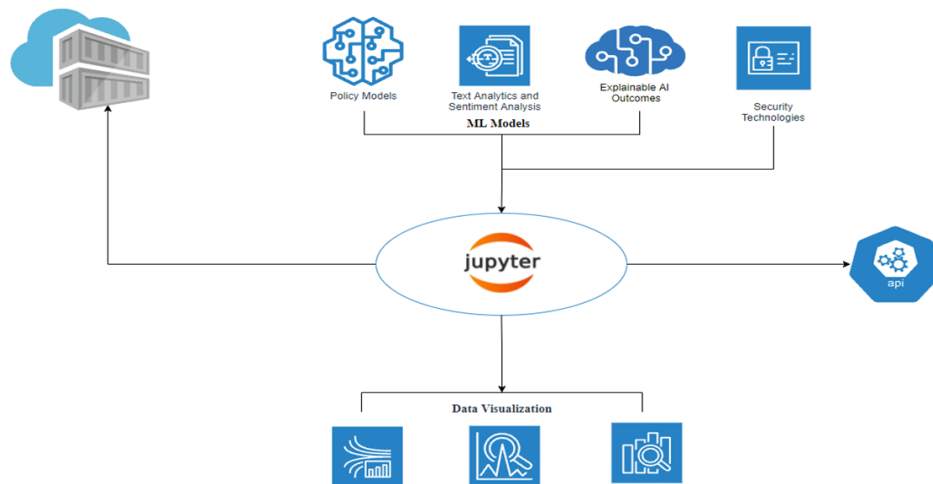


Figure 20. VPME subcomponents

3.4 AI4PublicPolicy Infrastructure

The AI4PublicPolicy services will be built on top of the multi-layered EOSC Compute Platform shown in Figure 21. Its main layers are:

- The **Federated Resource Providers** layer provides an Infrastructure-as-a-Service (IaaS) hybrid infrastructure from academic and commercial providers to run and/or host research applications and data. Its components are provided by cloud providers and High Performance Computing (HPC) centres from different European countries.
- The **Compute and Data Federation** layer provides advanced solutions for facilitating common and recurring tasks such as data management and transfer, virtual infrastructure orchestration and software distribution.
- The **Platforms** layer provides a higher abstraction layer on top of the previous one, offering generic Platform-as-a-Service (PaaS) services such as interactive notebook environment, machine learning and deep learning applications for data analysis, scalable big data tools, and workload management tools.
- The vertical **Service Management Tools** layer includes Helpdesk, Monitoring, Accounting, Operations Management, Security and Incident response, and Software Quality Assurance services.

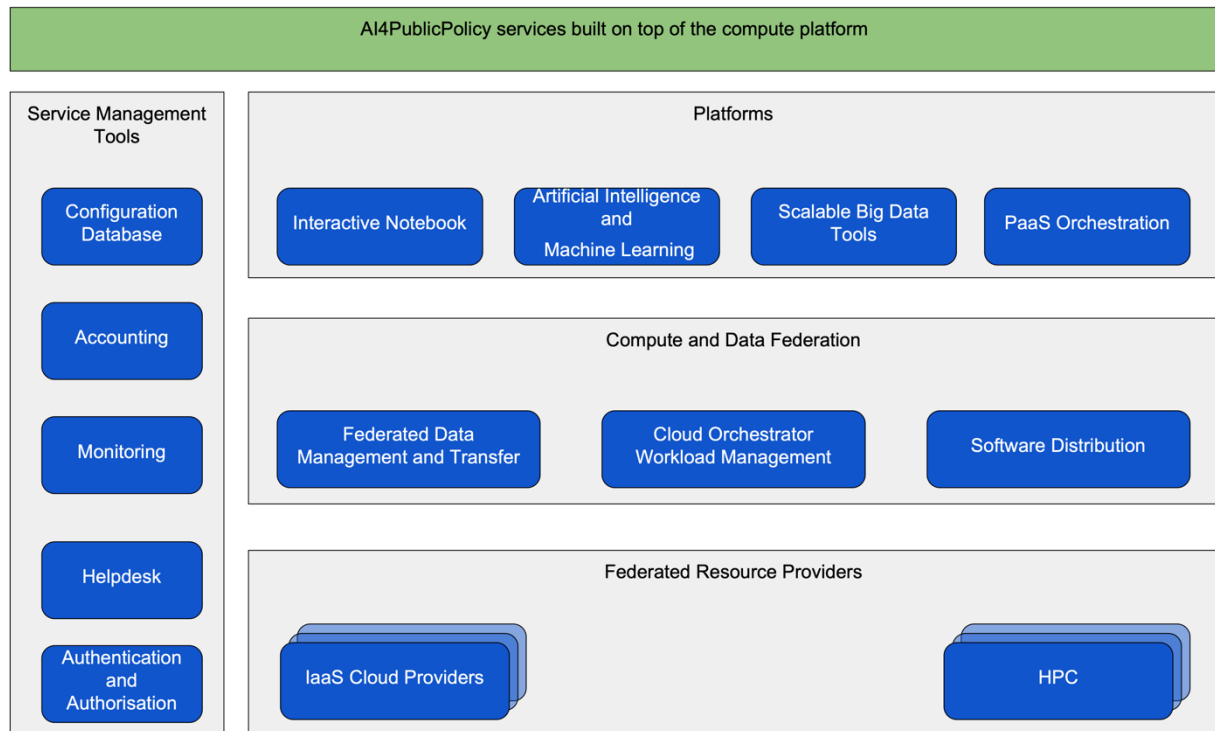


Figure 21. Infrastructure architecture

The infrastructure will provide technologies to allocate cloud and HPC resources like computing, data storing and sharing to facilitate the management of containers for the execution of the AI models created in the project. These resources will be offered through the European Cloud Initiative. EGI FedCloud services will be used where applicable.

The infrastructure is populated by data, applications, scripts, AI models etc. from project pilots and application developers.

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3.4.1 Service Management Tools

Access to datasets and applications hosted on the Compute Platform can be defined through Check-in, one of the main services provided by the Service Management Tools layer.

Authentication and Authorization: Check-in is the authentication, authorisation and user management service for the EGI infrastructure. It enables users to access EGI, and third-party services (web and non-web based), using existing credentials managed by the Identity Providers (IdPs) of their home organisations. The Check-in service enables users to:

- manage their accounts from a single interface
- link multiple accounts/identities together
- access services based on their roles and Virtual Organisation (VO)/group membership rights

3.4.2 Federated Resource Providers

The Federated Resource Providers layer is the bottom layer of the infrastructure providing computing and data resources both on cloud or HPC.

Cloud providers: Infrastructure-as-a-Service (IaaS) Cloud is provided by research cloud providers from many European countries and is based on OpenStack. It can be accessed through Check-in via web-dashboard, API and command line interface (CLI). They allow provision of low level storage such as block storage and object storage as well as Virtual Machines (VMs) and Kubernetes cluster among other things.

HPC: High Performance Computing (HPC) supports highly optimized applications that need massively parallel computing with low latency and high bandwidth interconnection networks such as complex computational problems using tightly coupled parallel processing: simulations, analysis of large datasets or AI workloads. It provides highly optimized computing systems that deliver large amounts of parallel computing power to run such applications and offers a managed service where you can find a fully operational environment where to submit your jobs. In most HPC systems, user access is performed via the Secure Shell Protocol (SSH) to a set of login nodes where users can interact with the system and submit jobs for their execution. In those providers who deliver HPC hardware via IaaS interfaces, an HPC system can be deployed using tools such as Elastic Cloud Compute Cluster.

3.4.3 Compute and Data Federation

The Compute and Data Federation layer provides advanced solutions to manage the resources available in the Federated Resource Providers layer such as the DataHub for the federation and management of data and the cloud orchestrators for the management of the compute resources.

DataHub: EGI DataHub is a federated service, integrated with EGI Check-in allowing users to access and share their data from anywhere using either fully restricted access based on access tokens or publicly shared data sets. EGI DataHub is provisioned based on the Onedata distributed data access and management system. Onedata is a globally distributed storage solution, integrating storage services from various providers using possibly heterogeneous underlying technologies

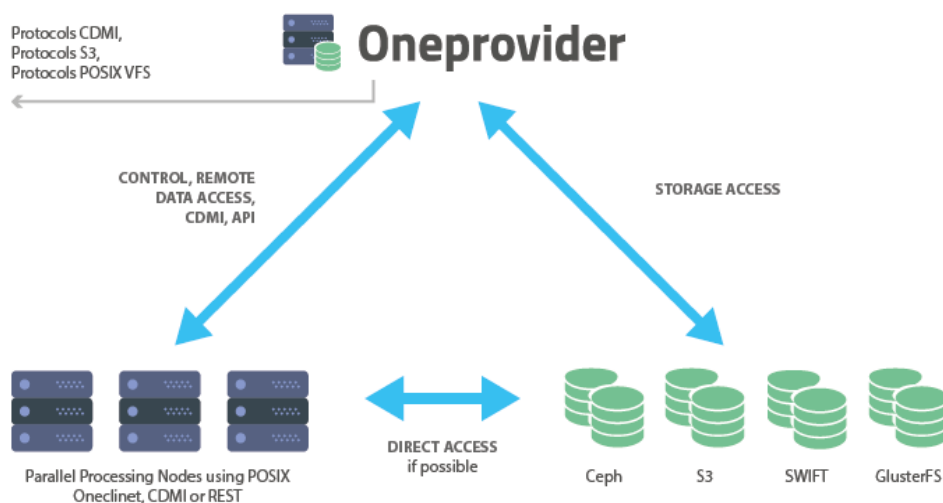


Figure 22. Federated resource provider layer

Onedata enables seamless sharing of data between users, with strict access control. Users can share access to individual files as well as spaces by sending automatically generated access tokens.

All Onedata components have APIs defined using OpenAPI specification version 2.0, enabling easy integration and automatic generation of client libraries for most existing programming languages and frameworks.

Infrastructure Manager: The IM Dashboard is designed to enable non advanced users to launch complex virtual infrastructures on top of a wide range of cloud providers (AWS, Google Cloud, Microsoft Azure, EGI Cloud Computing, OpenNebula, OpenStack, and more ...). Only with a few clicks the user can deploy the set of available topologies expressed through templates written in TOSCA (Simple Profile in YAML version 1.0). Then the IM service orchestrates the whole process: deployment of cloud resources, configuration, software installation, monitoring and update of the virtual infrastructures. Following is a list of functionalities provided by the Infrastructure Manager:

- OIDC authentication
- Display user's infrastructures
- Display infrastructure details, template and log
- Delete infrastructure
- Create new infrastructure
- Add nodes to an infrastructure
- Resize VMs
- Cloud resources

The entry web³ page for the tool is shown on the following screenshot:

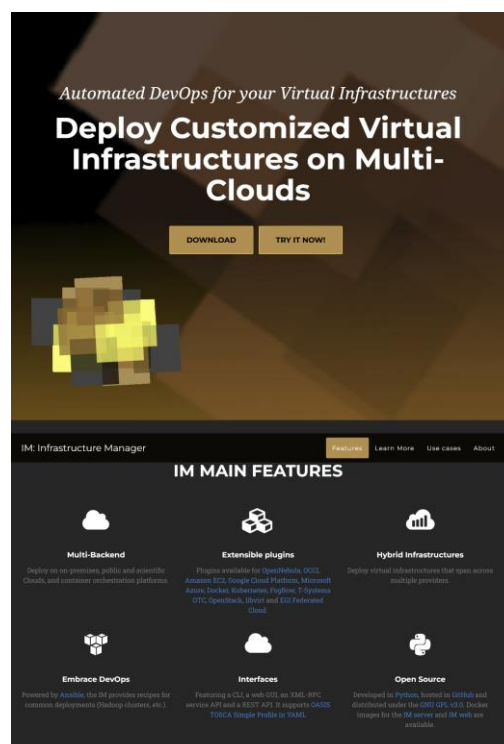


Figure 23. Entry web page screenshot

Elastic Cloud Computing Cluster: Elastic Cloud Computing Cluster (EC3) is a tool to create elastic virtual clusters on top of IaaS providers. Being based on Infrastructure Manager (IM) EC3 supports the same wide choices of back-ends. It offers recipes to deploy SLURM, Kubernetes, Apache Mesos and others. EC3 creates elastic cluster-like infrastructures that can automatically scale up or down,

³ <https://www.grycap.upv.es/im/index.php>

depending on demand and the configured policies. This creates the illusion of a real cluster without requiring an investment beyond the actual usage, delivering a cost-effective elastic Cluster-as-a-Service on top of an IaaS cloud.

3.4.4 Platforms layer

The Platforms layer is built on top of the federation, either by using IaaS APIs or Federated IaaS provisioning, and can provide community-specific data, tools and applications. Two relevant services are notebooks and the DEEP training facility.

Notebook: Jupyter Notebook complemented with Binder allows users to create data and code-driven narratives made of interactively executable code, equations, descriptive text, interactive dashboards and other rich media. Its integration with the other services of the computing platform, from check-in to datahub, allows to easily build a community interactive notebook environment, with a fine-grained control on user access, and the possibility to access and share stored data.

DEEP training facility: Distributed training facility for Machine Learning, Artificial Intelligence and Deep Learning models. This service offers a set of tools to build and train Machine Learning, Artificial Intelligence and Deep Learning models in distributed e-Infrastructures. Ready to use models are available for transfer learning or reuse. The DEEP-Hybrid-DataCloud is providing machine learning and deep learning scientists with a set of tools that allow them to effectively exploit the existing compute and storage resources available through EU e-Infrastructures for the whole machine learning cycle. The DEEP training facility provides tools for building training, testing and evaluating Machine Learning, Artificial Intelligence and Deep Learning models over distributed e-Infrastructures leveraging GPU resources. Models can be built from scratch or from existing and pre-trained models (transfer learning or model reuse). Features: - Transparent training over distributed e-Infrastructures with GPU access. - Docker based for model portability and reusability. - Easy model integration with standards-based REST APIs. - CLI and web user interface to interact with the system.

4 Validation Matrix

The next table presents the validation matrix that shows which components are used by each User Story defined for different pilots. The User Stories are the ones defined in deliverable D2.1 Use Case Scenarios Definition and Design.

This Matrix was used to validate the architecture and the technical requirements of each component towards the business requirements.

Table 1. Validation matrix

| User Story # | Pilot | VPME | Policy Evaluation & Optimization | Policy Extraction | Text & Sentiment Analysis | AI Security | AutoML | Policy Explainability & Interpretation | Semantic Interoperability | Datasets & Policy Catalogue | Cross Country Interoperability | Dataset Collection & Management |
|--------------|--------|------|----------------------------------|-------------------|---------------------------|-------------|--------|--|---------------------------|-----------------------------|--------------------------------|---------------------------------|
| US01 | Athens | • | | • | | | • | • | • | | | • |
| US02 | Athens | • | | • | | | • | • | • | | | • |
| US03 | Athens | • | | • | | | | • | • | | | • |
| US04 | Athens | • | • | | • | | | | • | | | • |
| US05 | Athens | • | | • | | | • | | • | | | • |
| US06 | Athens | • | | • | | | • | | • | | | • |
| US07 | Athens | • | • | | | | | | • | | | • |
| US08 | Athens | • | • | | | | | | • | | | • |
| US09 | Athens | • | | • | | | • | | • | | | • |
| US10 | Athens | • | | • | | | • | | • | | | • |
| US11 | Athens | • | • | | | | | • | • | | | • |
| US12 | Athens | • | • | | | • | | | • | | | • |
| US13 | Athens | • | • | | | | | | • | | | • |
| US14 | Athens | • | • | | | | | | • | | | • |
| US15 | Athens | • | • | | | | | | • | | | • |
| US16 | Athens | • | | • | | | • | • | • | | | • |
| US17 | Athens | • | | | | | | | • | | | • |
| US18 | Athens | • | | • | | | • | | • | | | • |
| US19 | Athens | • | | | | | | | • | | | • |

| User Story # | Pilot | VPME | Policy Evaluation & Optimization | Policy Extraction | Text & Sentiment Analysis | AI Security | AutoML | Policy Explainability & Interpretation | Semantic Interoperability | Datasets & Policy Catalogue | Cross Country Interoperability | Dataset Collection & Management |
|--------------|--------|------|----------------------------------|-------------------|---------------------------|-------------|--------|--|---------------------------|-----------------------------|--------------------------------|---------------------------------|
| US20 | Athens | • | | | | | | | • | | | • |
| US21 | Athens | • | • | • | | | • | | • | | | • |
| US22 | Athens | • | | | | • | | | • | | | • |
| US23 | Athens | • | • | | | • | | | • | | | • |
| US24 | Athens | • | | • | | • | • | | • | | | • |
| US25 | Athens | • | | • | | • | | | • | | | • |
| US26 | Athens | • | | • | | • | • | | • | | | • |
| US27 | Genoa | • | | | • | • | | | • | | | • |
| US28 | Genoa | • | | | | • | | | • | • | | • |
| US29 | Genoa | • | | | • | • | | | • | | | • |
| US30 | Genoa | • | | • | | • | • | • | • | | | • |
| US31 | Genoa | • | | | • | • | | • | • | | | • |
| US32 | Genoa | • | • | • | | • | • | • | • | | | • |
| US33 | Genoa | • | • | • | | • | • | | • | | | • |
| US34 | Genoa | • | • | | | • | | | • | | | • |
| US35 | Genoa | • | • | • | | • | • | | • | | | • |
| US36 | Genoa | • | | | | • | | | • | | | • |
| US37 | Genoa | • | | | • | • | | | • | | | • |
| US38 | Lisbon | • | | | | • | | • | • | • | | • |
| US39 | Lisbon | • | | | | • | | • | • | | | • |
| US40 | Lisbon | • | • | | | • | | • | • | | | • |
| US41 | Lisbon | • | | | • | • | | • | • | | | • |
| US42 | Lisbon | • | | • | | • | • | • | • | | | • |
| US43 | Lisbon | • | | • | | • | • | • | • | | | • |

| User Story # | Pilot | VPME | Policy Evaluation & Optimization | Policy Extraction | Text & Sentiment Analysis | AI Security | AutoML | Policy Explainability & Interpretation | Semantic Interoperability | Datasets & Policy Catalogue | Cross Country Interoperability | Dataset Collection & Management |
|--------------|--------|------|----------------------------------|-------------------|---------------------------|-------------|--------|--|---------------------------|-----------------------------|--------------------------------|---------------------------------|
| US44 | Lisbon | • | | | | • | | • | • | | | • |
| US45 | Lisbon | • | | | | • | | • | • | | | • |
| US46 | Lisbon | • | • | • | | • | • | | • | | | • |
| US47 | Lisbon | • | | • | | • | • | | • | | | • |
| US48 | Lisbon | • | | | | • | | • | • | | | • |
| US49 | Lisbon | • | | | | • | | | • | | • | • |
| US50 | Lisbon | • | | | | • | | | • | | • | • |
| US51 | Lisbon | • | | | • | • | | | • | | • | • |
| US52 | Lisbon | • | | | | • | | | • | • | • | • |
| US53 | Lisbon | • | • | | | • | | | • | | | • |
| US54 | Burgas | • | | • | | • | • | • | • | | | • |
| US55 | Burgas | • | | • | | • | • | • | • | | | • |
| US56 | Burgas | • | | | | • | | | • | | | • |
| US57 | Burgas | • | | • | | • | • | • | • | | | • |
| US58 | Burgas | • | | | | • | | • | • | | | • |
| US59 | Burgas | • | | | | • | | • | • | | | • |
| US60 | Burgas | • | | | | • | | | • | | | • |
| US61 | Burgas | • | | | | • | | | • | | | • |
| US62 | Burgas | • | | | | • | | • | • | | | • |
| US63 | Burgas | • | | | | • | | | • | | | • |
| US64 | Burgas | • | | | | • | | | • | | | • |
| US65 | Burgas | • | | | | • | | | • | | | • |
| US66 | Burgas | • | | | | • | | | • | | | • |
| US67 | Burgas | • | | | | • | | | • | | | • |

| User Story # | Pilot | VPME | Policy Evaluation & Optimization | Policy Extraction | Text & Sentiment Analysis | AI Security | AutoML | Policy Explainability & Interpretation | Semantic Interoperability | Datasets & Policy Catalogue | Cross Country Interoperability | Dataset Collection & Management |
|--------------|---------|------|----------------------------------|-------------------|---------------------------|-------------|--------|--|---------------------------|-----------------------------|--------------------------------|---------------------------------|
| US68 | Burgas | • | | | | • | | • | • | | | • |
| US69 | Burgas | • | | | | • | | | • | | | • |
| US70 | Nicosia | • | • | • | • | • | | | • | • | • | • |
| US71 | Nicosia | • | • | • | • | • | | | • | • | • | • |
| US72 | Nicosia | • | | • | | • | • | • | • | | | • |
| US73 | Nicosia | • | | • | | • | • | • | • | • | • | • |
| US74 | Nicosia | • | • | • | • | • | | | • | | | • |
| US75 | Nicosia | • | | • | | • | • | • | • | | | • |

This validation matrix will evolve in the future as the user stories are refined. Future versions of this document will capture the final usage of components by each use case.

5 Scenarios

This section presents a set of scenarios which describes how the end users (Policy Makers, AI Expert, Stakeholders) interact with the components of the AI4PublicPolicy Reference Architecture, described in chapter 3, to implements the main steps of the Policy Making Process as described in chapter 2.

5.1 Policy Definition

A policy maker wishes to develop a Policy using an AI-driven approach.

1. The policy maker creates a Policy describing the context and the problem
2. The policy maker adds relevant Datasets to the Policy and describe them
3. The policy maker changes the status of the Policy to “Modelling”

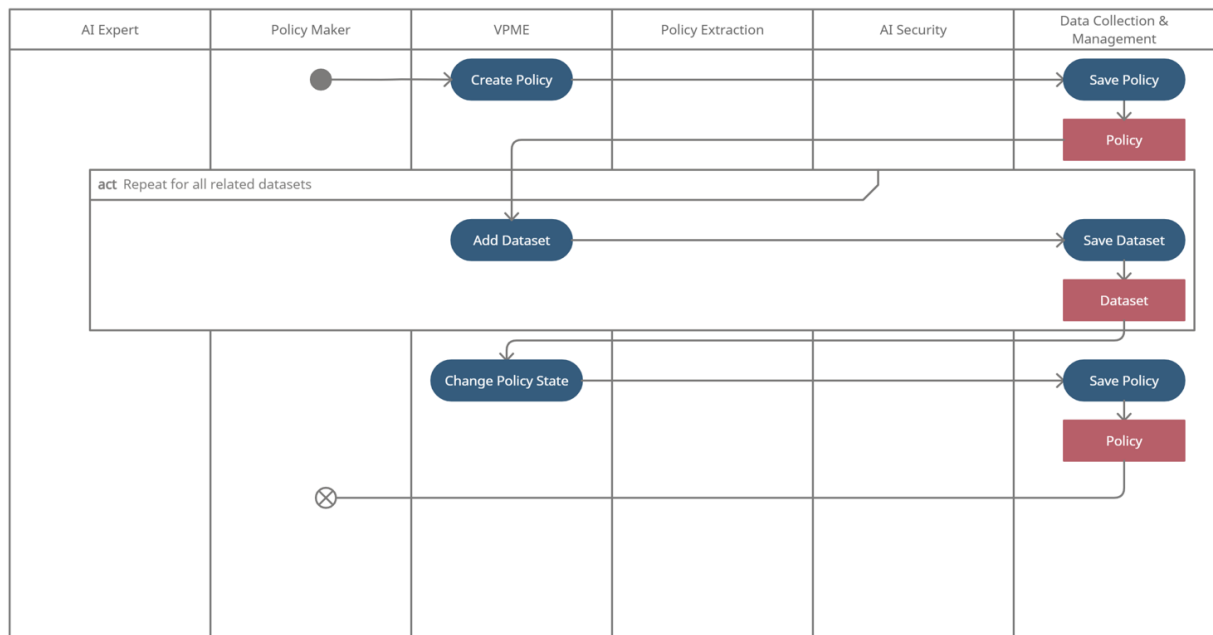


Figure 24. Policy definition interaction diagram

5.2 Policy Extraction

An AI Expert wishes to create different AI workflows to test different AI Algorithms for a Policy over one or more Policy Datasets.

1. The AI Expert selects a “Modelling” Policy
2. The AI Expert creates a set of AI Workflow with different AI Algorithms and Tools to address the problem described in the Policy
3. The AI Expert runs the AI Workflows on one or more Policy Datasets and trains a set of AI Models
4. The AI Expert tests and validates the AI Models or changes the AI Workflows

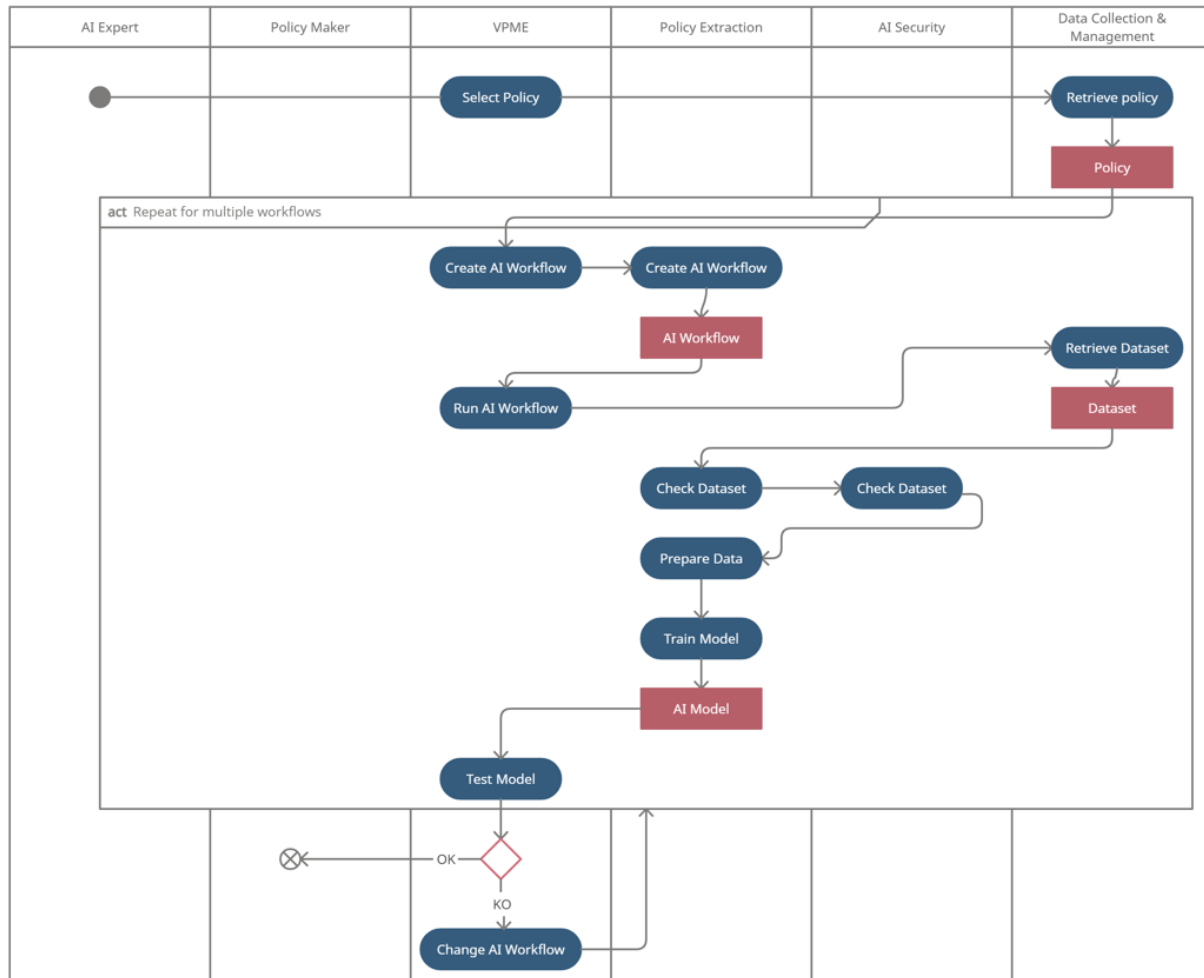


Figure 25. Policy extraction, create AI workflows interaction diagram

A Policy Maker wishes to receive a policy response for a given policy and the AI model.

1. Policy Maker selects a Policy
2. Selects an AI Model (from that list of available models for that policy)
3. Runs the AI Model
4. Receives a Policy Response
5. Updates the Policy State
6. Saves the Policy

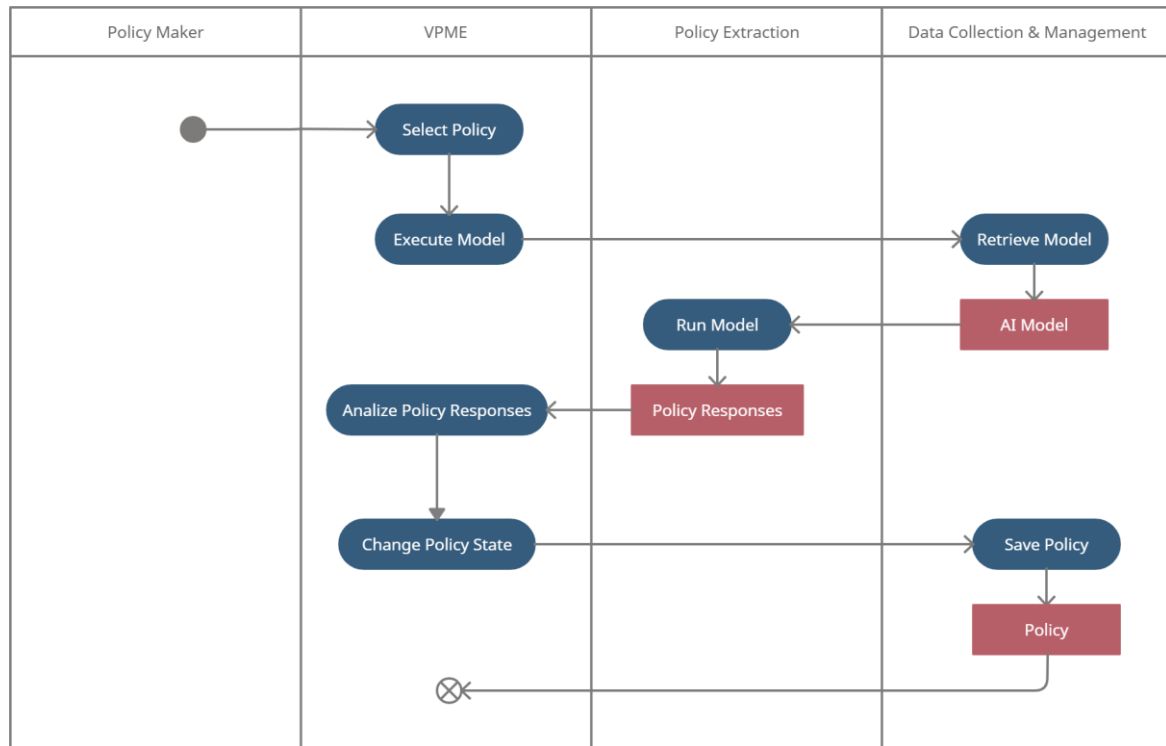


Figure 26. Policy extraction, receive policy response interaction diagram

5.3 Policy Evaluation

Feedback (opinions) from citizens affected by a policy is collected for policy evaluation and optimization.

1. The Policy Maker selects a Policy in “Evaluating” state
2. The Policy Maker creates a survey for the Policy specifying the survey type, questions, options and the output channel
3. The Policy Evaluation Component creates the survey and publish it on the selected channels
4. The relevant Stakeholders receive a notification and answer the survey on the specific channel
5. The Policy maker select an active survey an request the results
6. The Policy Evaluation Component close the survey and collect the feedbacks
7. The Policy Evaluation Component elaborates the result of the survey as a statistical score and call the Text and Sentiment Analysis Component to evaluate a sentiment score
8. The Policy Maker evaluate the survey result and change the Policy status accordly

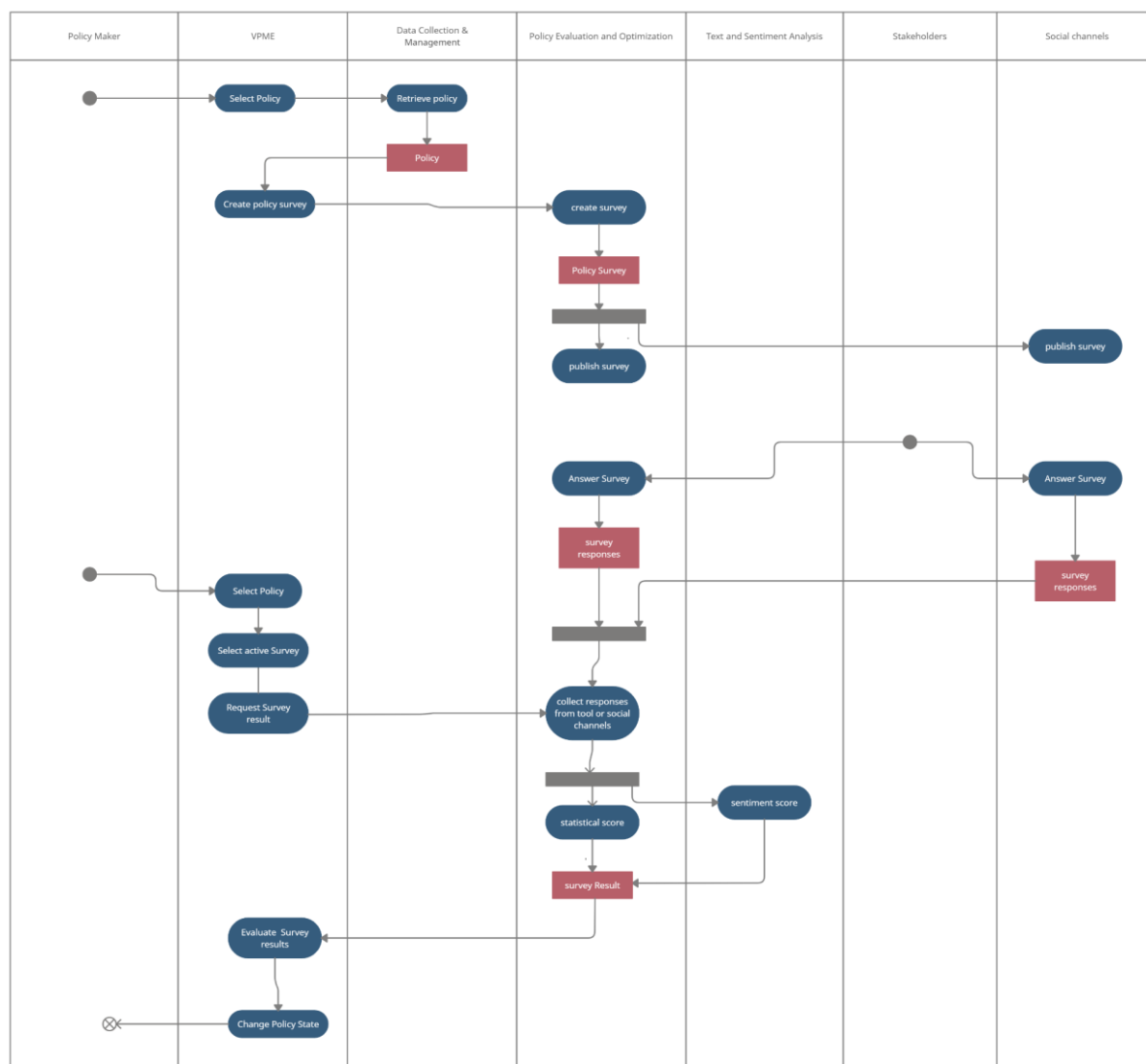


Figure 27. Policy evaluation interaction diagram

5.4 Policy Interpretation/Presentation

A policy maker needs to understand the rationale behind the results of the forecast of a given policy (AI model), if the predictions were accurate, the contribution of each variable to the prediction, and their relationship. The steps the policy makes are:

1. The policy maker selects a model (e.g., based on regression) and a data set
2. A default interpretation dashboard is generated
3. The dashboard allows the user to browse the model performance, the features importance...
4. The policy maker browses the importance of different data features in the AI model.

The activity chart in Figure 28 shows this interaction and the components involved.

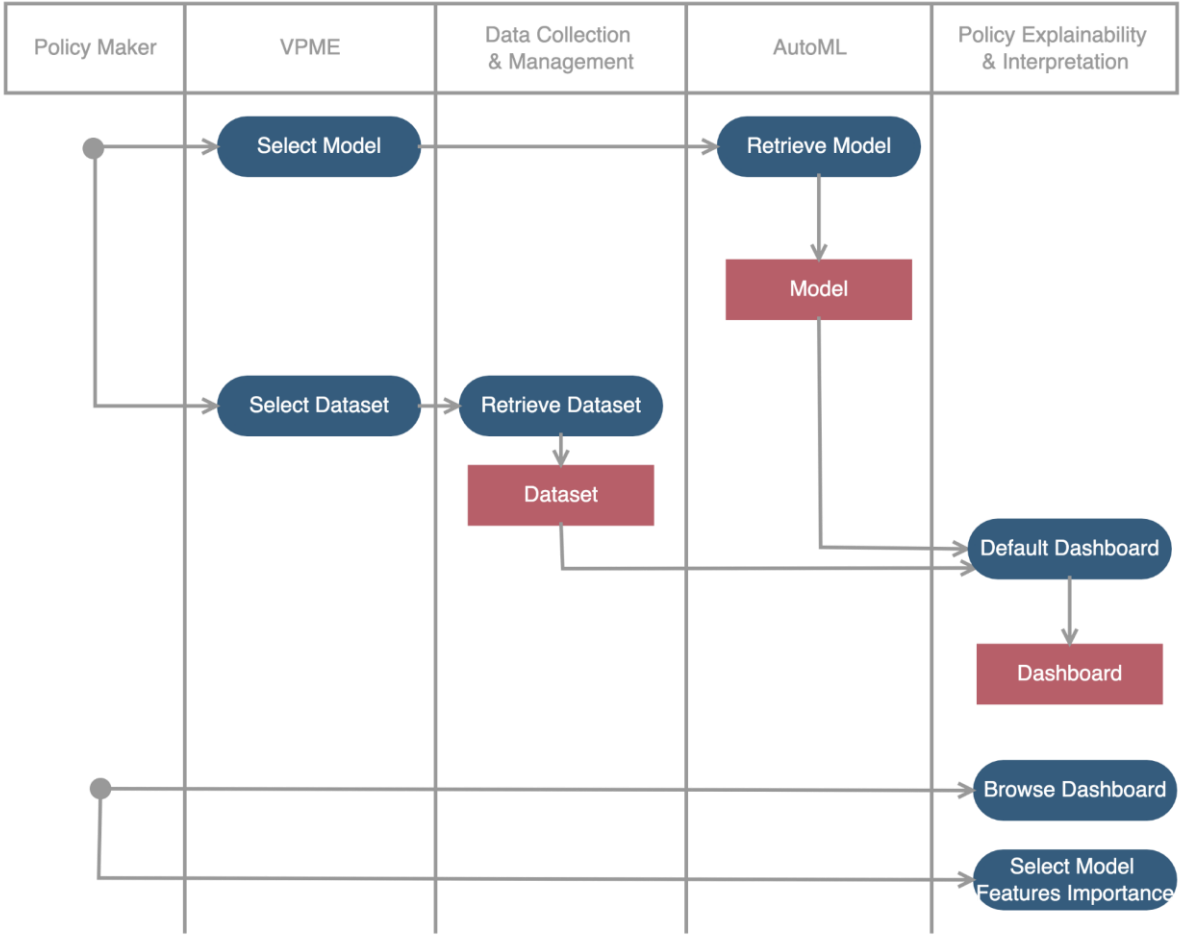


Figure 28. Policy Interpretation/Presentation interaction diagram

5.5 Data & Policy Sharing

A policy maker is aware of datasets for policies in different countries and wants to use them to run similar policies. The policy maker asks the data scientist to explore these data and train a model. The activity diagram in Figure 29 describes the components involved and the sequence of steps, summarised as:

1. The data scientist browses the dataset catalogue and selects a dataset.
2. The dataset is in a different language, the dataset is translated
3. The translated dataset is used to train a model

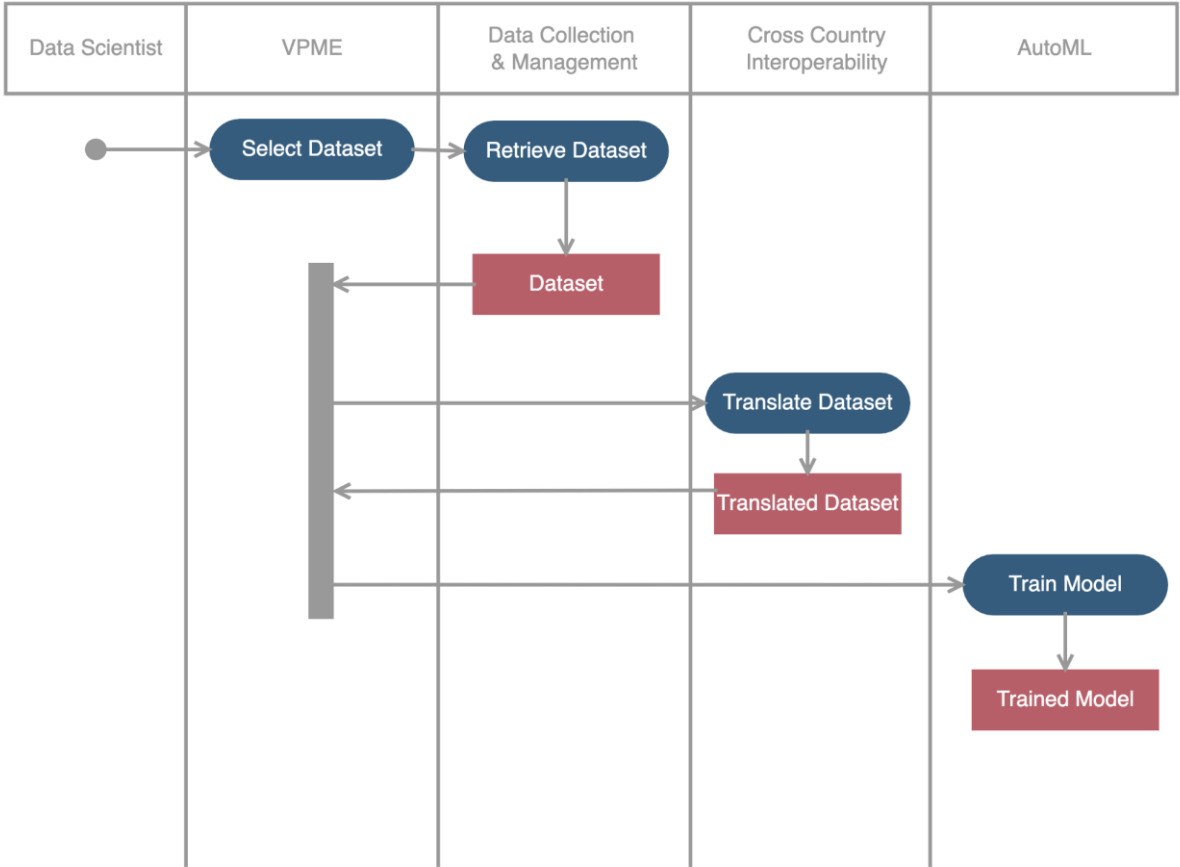


Figure 29. Data and policy sharing interaction diagram

6 Conclusions

This deliverable presents the initial description of the AI4PublicPolicy Conceptual Model and Reference Architecture. This includes the description of the AI-based Policy Making Process, based on CRISP-DM methodology, the description of the main components and their interactions and the description of the cloud infrastructure.

Finally, the adherence of the RA to the Pilots User Stories collected in deliverable D2.1 and to the steps of the AI-based Policy Making Process is presented through a validation matrix and a set of scenarios.

An updated version of this deliverable will be delivered in month 18. This new version will update the architecture based on the results usage of the first prototype of the platform by the use cases.

7 References

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