Data-driven policy development of Municipalities
Preparation steps for Integrating AI tools in the policymaking process

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Keywords: Public Administration, Digital Transformation, Artificial Intelligence, Virtualised Policy Management Environment, Data-Driven Policy Development, Horizon 2020 Research & Innovation

Abstract

This paper draws from the experience of the 3-year, Horizon 2020 project, AI4PublicPolicy, and examines the essential actions public municipalities should take to adequately prepare for the integration of Artificial Intelligence (AI) into their policy making processes under the scope of the five pilot cities involved in the project. The study explores a range of issues including organisational, technological, and ethical aspects. It also underlines the importance to understand local environments, involve stakeholders, evaluate the relevance and the availability of the data, assess the technological readiness, improve internal capacities and assure legal and ethical compliance. In order to promote transparency and cultivate public trust, the document also emphasizes the significance of elaborating on user-centric, agile and stable AI-based tools and solutions, such as dashboards of Explainable AI (XAI) services. Municipalities may pave their way towards automated, transparent and citizen-centric development of public policies by handling the challenges of AI deployment with the help of the current framework.

1. Introduction

1.1 Importance of AI in Policy-making process

The integration of AI into policymaking signifies a significant shift in local government decision-making. AI's potential to revolutionize policy development, implementation, and evaluation underscores its importance. It promises to enhance public services, boost efficacy, efficiency, and transparency in policy development, and streamline every stage of the policy cycle, from agenda-setting to assessment (Wirjo et al., 2022) and (Patel et al., 2021).

AI facilitates **data-driven policy development** by analysing vast datasets from various sources, enabling informed decisions through pattern recognition and trend identification (Charles et al., 2022). This integration goes beyond data presentation, providing policymakers with insights into social trends and preferences for evidence-based policymaking.

Furthermore, local governments and policymakers could utilize **predictive analytics** to anticipate future trends, streamline planning, and allocate resources more effectively through analysis of historical data (International Association of Business Analytics Certification, 2023).

AI solutions could also aid local authorities in **enhancing efficiency and effectiveness** by automating routine tasks and streamlining daily processes more efficiently.

Furthermore, AI, both generally and within the AI4PublicPolicy Project, could enable policymakers to **simulate policies** by exploring various scenarios within a Virtualised Policy Management Environment (hereafter VPME)[1].

Moreover, implementing AI solutions could enhance **transparency** by utilizing Explainable Artificial Intelligence (XAI) to elucidate how AI models operate, offering human-understandable explanations (Vyas, 2023). This fosters greater public trust by making AI decisions more comprehensible.

Overall, integrating AI technologies can significantly enhance local governance efficiency, improve decision-making, engage citizens, build public trust, and address societal challenges more efficiently.

1.2 The AI4PublicPolicy project value proposition

Supported by the European Union's Horizon 2020 Research and Innovation programme (GA No. 101004480), AI4PublicPolicy is a 3-year collaborative action that brings together policy makers with Cloud/AI experts to introduce a novel, Open Cloud platform, called **Virtualised Policy Management Environment** (VPME). The AI4PublicPolicy VPME employs AI technologies such as Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), to **automate, scale, and enhance transparency in public policy management**. The VPME seeks to innovate **the entire policy development cycle** based on technologies for the extraction, simulation, evaluation and optimisation of interoperable and reusable citizen-centric public policies.

The project is positioned at the core of the European Union's vision to bring data-driven, user-centric, agile and transparent digital technologies to businesses, citizens and public administrations going beyond the narrowly operationalized and IT-focused approach[2]. In this context, **the AI4PublicPolicy constitutes a founding member of the Data-Driven Policy Cluster** of EU-funded projects that consists of several cross-European collaborations that work on mainstreaming the evidence-based policy making thought the integration of AI and Big Data into the digital transformation of public administration, the introduction of automation in administrative workflows, the strengthening of regulatory frameworks and the enhancement of civic engagement and participation.

1.3 Objective of the paper

This paper aims to provide a ground-setting overview for public authorities (i.e., municipalities) to effectively embark upon AI-based solutions in policymaking, drawing from the experiences of the AI4PublicPolicy project. It presents a comprehensive

[1] https://ai4publicpolicy.eu/ai4pp-vpme/

[2] https://digital-strategy.ec.europa.eu/en

framework for integrating AI technologies into policymaking procedures, emphasizing the importance of a holistic approach. By considering organizational capacity, technology readiness, and ethical considerations, this framework facilitates the transition from traditional to AI-enabled policymaking, enhancing effectiveness, transparency, and citizen-centric governance.

2. AI4PublicPolicy AI-driven policy-making process

2.1 The CRISP-DM methodology[3]

AI4PublicPolicy adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology to collaboratively develop data-driven policies, involving stakeholders from policymakers to citizens for transparency and acceptance. This six-step process includes understanding business objectives, collecting and preparing data, applying modelling techniques, evaluating models against objectives, and deploying them for decision-making. This approach promotes evidence-based policymaking and enables model and dataset sharing among authorities.

Data collection and management: In the initial stage of data collection and management, local authorities must assess available datasets from various sources and select relevant ones for testing and implementing policy ideas.

Policy and datasets definition in the VPME: Once relevant datasets are collected, policymakers and experts begin crafting an Analytical Policy Model within the VPME platform. This model outlines policy problems and associates relevant datasets, while also defining Key Policy Indicators (KPIs) for each policy. This process is facilitated by the Policy and Datasets Management Component on the VPME platform.

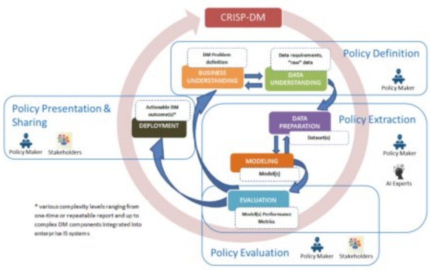

Figure 1. Policy Development Cycle.

Policy extraction: Once policies and datasets are defined, AI experts utilize the Policy Extraction Component to create AI models and dashboards. Using Auto Machine Learning (AML), they develop workflows to analyze datasets, train and test AI models with various algorithms, and provide insights and recommendations for policy problems. Policy makers execute AI models on new data, analyze responses, and validate models. Dashboards are then created for each KPI, tailored for effective representation and comprehension based on the data type and layout considerations.

Policy evaluation: In the final step, the policymaker engages stakeholders through surveys on policy problems, AI model responses, and alternatives. Stakeholder feedback, evaluated with statistical or sentiment scoring, informs decisions to finalize policies with actionable outcomes or optimise them based on feedback.

Policy presentation and sharing: In this final step the policymaker uses XAI techniques provided by the platform to better understand and explain the rationales under the AI models responses. Once completed this step the policymaker could present the final Analytical Policy Model, which represents the result of the AI-based Policy Making Process, to the relevant stakeholders and publish it in the shared catalogue[4].

The AI4PublicPolicy's workplan was streamlined based on the CRISP-DM methodology so that a data-driven approach was followed by the project's pilots through the entire project lifecycle. The pilots' preparation, deployment and validation of the AI4PublicPolicy novelties represents a significant advancement in policymaking, empowering policymakers with a data-driven approach.

3. Pilot sites framework preparation for AI implementation in the policy-making process

3.1 Pilot infrastructure, data availability and local systems preparation

This chapter outlines the preparatory efforts undertaken by each pilot according to the project's implementation to ensure successful implementation of AI tools for transitioning to AI-based policy development. It covers issues such as dataset availability and relevance, hardware and software requirements for data collection, integration of local systems, equipment availability, training and capacity building strategies, stakeholder engagement, communication strategies, and completion of ethical activities for legal and ethical compliance.

3.1.1 Data availability and relevance

3.1.1.1 Hardware/software for data collection

Initially, pilots identified and described the equipment required for data collection activities. This included detailed information on hardware and software used to ensure transparency and enable replication in other cities. Pilots acted diligently in installing, maintaining, and upgrading equipment and software as project requirements evolved.

3.1.1.2 Historical data accessibility

Pilots established procedures for technical teams to access historical datasets. Clear protocols and guidelines enabled pertinent access to historical data, provided in various formats and fully anonymised in accordance with the datasets requirements specified in the relevant project deliverable, *D2.3 Datasets and policies data models*[5]. Questionnaires were circulated to gather comprehensive information on available data sources, vital for identifying best practices and defining data models driving the policy management process in the AI4PublicPolicy platform.

3.1.1.3 Realtime data accessibility

Pilots specified hardware and software requirements for technical partners to access real-time data, which were stored locally on secure servers before dissemination. This centralized storage ensured data security and facilitated access through a shared network. Datasets were provided in stored formats like CSV or JSON, accessible via the VPME Dataset Management

[3] https://ai4publicpolicy.eu/the-crisp-dm-methodology-applied-in-ai4pp-policy-making/

[4] https://ai4publicpolicy.eu/catalogue-for-policies-datasets-component-part-1/

[5] https://zenodo.org/records/8026697

Component, or added to the VPME Policy and Dataset Catalogue[6] for wider access. Real-time data streams, subject to contractual agreements, were made accessible via REST APIs integrated with the VPME Dataset Management Component. Publicly available real-time datasets were also accessible through the Policy and Dataset Catalogue, ensuring broad usability.

3.1.1.4 Integration of legacy systems

Pilots evaluated the legacy systems that were in use and strategised their integration with AI4PublicPolicy pilot implementations. Seamless integration is crucial for leveraging existing infrastructure and maximizing the efficacy of AI-driven solutions in policymaking processes.

3.2 Capacity Building and Training

More than just pertinent data and technological preparedness are needed by public authorities for the successful integration of AI into policy making process. It demands careful planning as well as the building of municipalities' ability to use AI in the policy-making process. To this end, the pilots of the project crafted tailored training plans for each stakeholder group to ensure they understand AI concepts, the VPME and the AI tools in the policy-making process. Technical partners developed dedicated training materials for both technical and non-technical actors, including citizens, businesses, and domain experts. These materials, serving as documentation for the VPME platform, aim to foster utilization of project outcomes and build an ecosystem for policy management. They will be accessible via the AI4PublicPolicy marketplace[7].
For a successful training program, logistics and facilities are pivotal. Key considerations included the training venue, necessary equipment, materials, schedule, and establishing feedback mechanisms. Follow-up support was also deemed essential to ensure the effectiveness of the training for all involved partners.
Municipal staff actively engaged in validating VPME components, gaining practical AI tool experience in the AI4PublicPolicy project. Continuous learning is essential in the evolving AI field, ensuring administrators stay updated. By investing in capacity building and technology, municipalities unlock AI's transformative potential, transitioning smoothly to AI-based policymaking from legacy systems.

3.3 Stakeholders Engagement and Communication strategies

Early into the AI4PublicPolicy project, the pilots identified stakeholders such as policy makers, employees in public authorities of both administrative and ICT function, researchers from academic sector and citizens (i.e, civil/citizen groups, NGOs) and an involvement plan was crafted to engage them throughout the policy creation, development, and evaluation phases. This approach extended to the validation of technical solutions and exploration of business opportunities, with tailored plans for each stakeholder group based on their expertise. As the project evolved, ongoing identification and updating of relevant stakeholders remained a priority.
The co-creation activities of the pilot partners put emphasis on progressive evaluation and validation of the proof-of-concept (PoC) and the tentative releases of the AI-Based tools of the VPME, under the perspective of each pilot's scope.

Following closely the project's trajectory the dissemination and communication activities emphasised on demonstrating the VPME's prototype solutions and AI-based tools, the pilots' efforts to validate these components, as well as the related results and outcomes of this process. Hence, the dissemination and communication of the project focused on being more impactful towards specific target groups of the overall project community, that is, the researchers and AI experts, the decision/policy makers that come from the local public authorities in pilot sites and the representatives of local societies (i.e., NGOs and citizen groups and associations of relevance to each pilot's scope).

3.4 Ethical management actions

Deploying the project's technologies at a real scale with real data in real life, while being compliant with legal and ethics requirements, presented challenges with regard to: (1) people, (2) data and (3) co-creation policymaking.
Regarding the ethical involvement of people, the main challenge that policymakers face is to explain the relevance and potential impact of a new - technological and organizational - system to a diverse group of stakeholders. In this regard, digital literacy plays a crucial role. Technical jargon might sound intimidating and prevent adoption. Therefore, to stimulate people's engagement on a basis of awareness, the project pilots pinpointed what aspects of the new digital process to communicate, made concrete examples, and showed possible outcomes in an iterative and informed circular process.
Secondly, the quality and availability of data represent a clear organisational, and often legal, challenge for public administrations. This requires the establishment of processes and the availability of technical skills. In practice, the pilots opted for a solution to map available data, identifying who is in control and how and to what extent the necessary data is available. Hence, specific use cases could be created. It should be stressed at this point that, a use case built on scarce or low-quality data might trigger serious ethical and legal concerns.
Thirdly, the implementation of co-creation activities (powered by digital tools) is often limited by established and institutionalized practice. The introduction of a tailored co-creation approach within the project's context required time and perseverance by the pilots, and was defined within specific instances, in which the ordinary policymaking process can be improved either from an ontological perspective (e.g. gathering of new or better information) or from an executive perspective (e.g. providing better execution plans).
All in all, AI4PublicPolicy can be an opportunity for public administration to comply with their transparency and accountability obligations, support Open Data initiatives across Europe and support the exchange of best practices and experiences among policymakers, while ensuring the right to a good administration, as envisaged in Art. 41 of the Charter of Fundamental Rights of the European Union.

4. Pilots' case studies

4.1 Lisbon, Portugal

4.1.1 Pilot Use Case – Renewables photovoltaic systems' potential and performance analysis

The Lisbon pilot utilized AI and machine learning to address energy efficiency challenges by analysing local energy data. By

[6] https://ai4publicpolicy.eu/catalogue-for-policies-datasets-component-part-1/
[7] https://market.ai4publicpolicy.eu/

https://doi.org/10.5194/isprs-archives-XLVIII-4-W10-2024-85-2024

identifying patterns and inefficiencies, it aimed to develop data-driven policies for sustainability. This aligned with Lisbon's commitment to the Covenant of Mayors for Climate and Energy and its goal of carbon neutrality by 2050. The use case focused on analysing photovoltaic systems' (PV) potential and performance, utilizing datasets like orthophotomaps and satellite images. It also, provided tools to monitor energy production and forecast scenarios, informing stakeholders and citizens about potential cost savings from adopting PV systems.

4.1.1.1 Pilot Policy – PV systems mapping for a climate neutral city

The Lisbon pilot evaluated solar energy adoption using key performance indicators (KPIs) and AI models. KPIs included the number of PV installations, installed capacity, progress towards the 2030 goal, and comparison with theoretical potential. Two core AI models, Yolov8 for object detection and Unet for image segmentation, were utilised to estimate these KPIs. The dashboard displayed total PV installations in Lisbon, broken down by parish, and ranks top parishes. Users could visualise detected PV installations' locations, with aggregated amounts at lower zoom levels and exact locations at higher zoom levels.

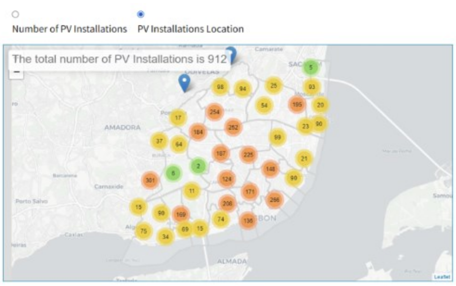

Figure 2. Mapping of PV installations dashboard

4.2 Burgas, Bulgaria

4.2.1 Pilot Use Case - Data-driven maintenance of the water pipe infrastructure

The Burgas pilot, a collaboration between Burgas Municipality and EKSO S.R.L, utilised AI and sensor technology to improve water pipe infrastructure maintenance in Burgas areas. Vibration sensors along 'Dr. Nider Street' detected leaks in near real-time and optimised maintenance schedules using historical data. In collaboration with the Water Supply and Sewerage Company (WSSC), the project set a precedent for scaling AI-driven solutions across the city's water distribution system, potentially extending to other liquid-carrying pipes.

4.2.1.1 Pilot Policy - Leak detection

The first policy of the Burgas pilot employed AI and sensor technology for leak detection in water pipe infrastructure. Vibration sensors on 'Dr. Nider Street' enabled near real-time leak detection, with the AI model achieving an 85% accuracy rate. The relevant objectives included improving reaction time to network failures, reducing water losses, and optimising maintenance planning. The key performance indicator set was the number of alerts triggered by the AI model indicating leaks. The policy dashboard displayed sensor data and AI predictions, with future enhancements targeting false alarms, improved leak localisation, and enhanced dashboard functionality for replication across different pipe networks.

Figure 3. AI-based model for leakage detection - results when a leakage was simulated in the pipe

4.2.2 Pilot Use Case – Identification of zones with water delivery failures

The second use case created an asset management tool to pinpoint areas with frequent water delivery failures and categorise them in color-coded circular zones corresponding to the incident rate in the area. Medium degree zones were coloured in yellow and were mapped between 80m of at least two points of water failures over the given period. Zones with a high degree of failures were coloured in red and are those whose points are within 80m of at least three points of water failures over the given period.

4.2.2.1 Pilot Policy - Pipe Maintenance and Replacement Optimisation

The second policy targeted pipe maintenance and replacement optimisation by pinpointing areas with past water service disruptions. It prioritised zones needing urgent attention based on historical failure data, in order to minimize disruptions, boost customer satisfaction, and streamline repair schedules. The AI model, utilizing incident reports, identified high-priority areas for pipe replacement. The dashboard visually represented repair works and highlights priority zones, aiding engineers in efficient maintenance planning.

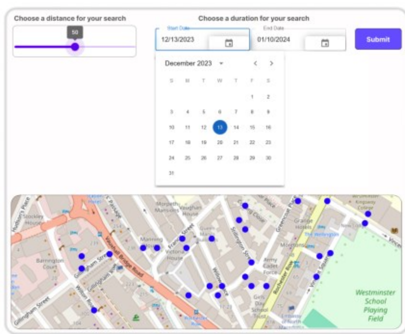

Figure 4. Pipe maintenance and replacement dashboard

4.3 Athens, Greece

4.3.1 Pilot Use Case - Maintenance policies optimisation

The Maintenance Policies Optimisation use case aimed to create and validate policies for efficiently allocating maintenance resources and scheduling activities in the city. This involved considering various factors like infrastructure type, repair time, maintenance frequency, bottlenecks, and citizen feedback on satisfaction.

4.3.1.1 Pilot Policy – Maintenance incidents prediction for planning purposes

The first policy of Athens pilot predicted maintenance incidents to plan ahead for material purchases and personnel allocation effectively. This aimed to optimise resources, reduce resolution time, and boost citizen satisfaction. Two AI models were created: one predicted top issues with 74% accuracy, while the other forecasted monthly issue numbers per authority service with a relative absolute error of 35%. The maintenance officers could use a dashboard to input service and timeframe for incident prediction and planning.

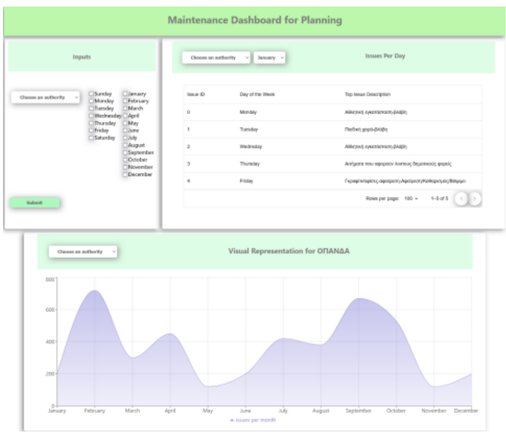

Figure 5. Maintenance optimisation dashboard

4.3.2 Pilot Use Case – Predictive and citizen-centric transport/parking policies development

This use case employed AI analytics over transport data (notably parking information) to forecast parking availability citywide. This guided policy makers in reallocating parking spaces to enhance coverage, revenue, and citizen satisfaction by reducing search time and improving availability. The VPME tools recommend optimal parking locations, refined by citizen feedback, for better policy implementation.

4.3.2.1 Pilot Policy – Parking space allocation optimisation

The optimised parking space allocation in Athens aimed to distribute on-street parking between residents and visitors for maximum revenue and satisfaction. AI analytics identified high-demand areas, offering real-time availability information. A deep neural network model predicted available spaces and profit, providing zone-specific insights and allocation suggestions via dashboards.

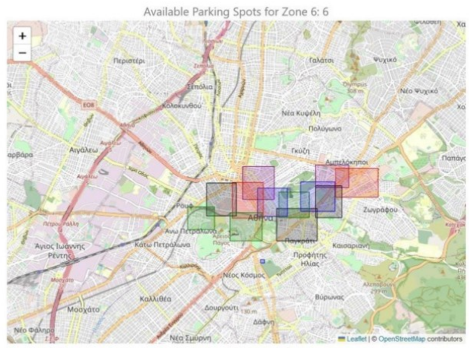

Figure 6. Parking zones' availability forecast dashboard

4.4 Genoa, Italy

4.4.1 Pilot Use Case – Reducing road accidents against vulnerable people

Genoa's pilot aimed to integrate AI into policymaking to tackle road accidents and urban safety, focusing on vulnerable groups such as children, adolescents, the elderly, cyclists, pedestrians, and motorized two-wheelers. The use case's context drew from and aligned with the National Road Safety Plan's aim of reducing accidents by 50% by 2030 and eliminating them by 2050.

4.4.1.1 Pilot Policy – Pedestrian crossings with the most urgent need for improvements

Genoa Municipality aimed to enhance pedestrian crossings to boost urban safety. In this pilot policy, crossings were categorised by risk level, and solutions prioritized accordingly to increase safety measures and prevent accidents. The policy employed a Pedestrian Crossing Urgency Index, using an AI model trained on classified crossings to predict urgency levels. A dashboard assisted local authorities in visualising, adjusting features, comparing, and ranking crossings so that they can prioritise the areas for intervention.

This contribution has been peer-reviewed.
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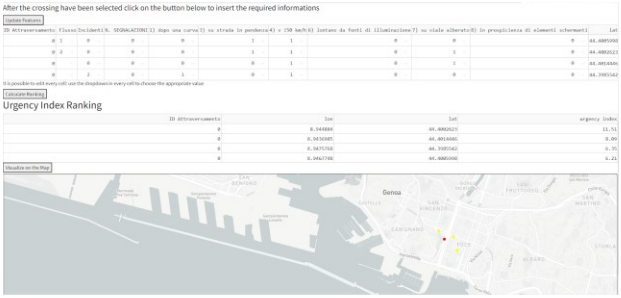


Figure 7. Dashboard of pedestrian crossings urgency index

4.4.1.2 Pilot Policy - Determining the danger index of city areas

The second pilot policy aimed to assess urban hazard indices for vulnerable groups using factors like weather, traffic, and road structure, aiming to minimise accidents involving these populations. The policy utilised a Road Accident Risk Indicator, reflecting accident probabilities for vulnerable subjects based on time, date, and weather. An AI model, LSTM-GNN, trained on composite data integrated city graphs, GIS points, and historical meteorological and accident data. A dashboard displayed Genoa's map divided into zones, highlighting accident risk indices based on forecasted weather conditions for selected dates and times, allowing users to zoom in for detailed zone-specific risk assessment.

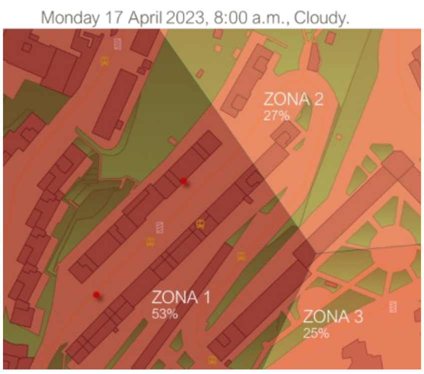


Figure 8. Dashboard of danger index across city's zones

4.5 Nicosia, Cyprus

4.5.1 Pilot Use Case - Optimal urban mobility policies for citizens

The Nicosia Pilot aimed to create evidence-based policies using traffic and public transport data to reduce citizen travel time across different modes of transportation. It also sought to raise awareness among citizens, promoting informed commuting choices to improve environmental performance and overall mobility in the city.

4.5.1.1 Pilot Policy - Improved accessibility of people with disabilities

The first pilot policy enhanced the accessibility for people with disabilities by allowing their access to restricted streets during traffic congestion through automated whitelists and AI analysis. Data coming from LPR cameras installed in three spots in 'Makariou Street' and a whitelist database were used in conjunction prioritise vulnerable people's passage, improving traffic flow. A deep learning model predicted traffic levels on the 'Makariou Street', categorised into three levels: no traffic, moderate traffic, and heavy traffic. A dashboard integrated models for informed decisions on allowing vehicles into restricted streets during congestion.

Figure 9. Line chart of traffic around 'Makariou Street' and concurrent vehicles' number

4.5.1.2 Pilot Policy – Smart parking management for people with disabilities

The second pilot policy employed advanced AI to predict parking availability for individuals with disabilities in Nicosia, enhancing urban accessibility. It aimed to reduce frustration, improve compliance with regulations, and inform future urban planning efforts. A deep learning model trained with extensive datasets gathered form the Nokia platform[8], offered granular predictions based on time inputs, optimising parking resource utilization. The model's predictive capabilities extended beyond mere binary predictions of parking availability, because it leveraged the temporal dimensions of month, day, and hour, thus being able to provide nuanced insights into the precise number of free parking spaces within specific zones. An interactive dashboard enabled real-time location of available parking spaces, streamlining the parking experience and reducing congestion.

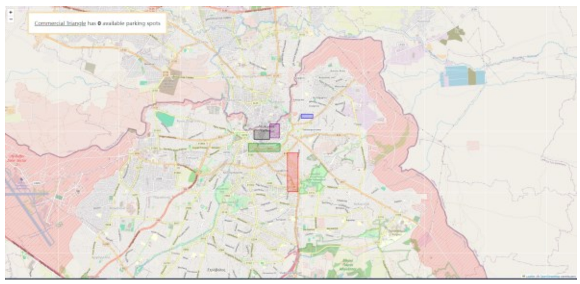


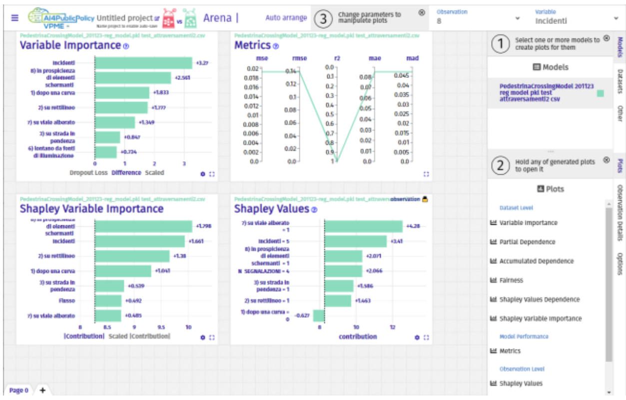
Figure 10. Dashboard for the smart parking management for people with disabilities policy

4.6 Pilots' Explainable AI Dashboards

In addition to the above-described main policy management dashboards, explainable AI (XAI) dashboards were developed in the context of the pilots' use cases. The XAI dashboards offer users a clear insight into how an AI model makes predictions by highlighting the importance of each variable and its role in decision-making. Through the utlisation of the Arena component[9] XAI dashboards were set so that users can explore variable contributions, adjust scales, and compare values, gaining a detailed understanding of prediction influences.

[8] https://www.nokia.com/about-us/news/releases/2021/03/31/nokia-selected-by-cyta-for-nicosia-integrated-operations-center-deal/
[9] https://arenar.drwhy.ai/

Tailored charts provided further insights, enhancing comprehension of prediction mechanisms.
For example, the XAI dashboard for Genoa's pilot policy on mapping the pedestrian crossings with the most urgent need for maintenance provided the Municipality with insights into the policy's decision-making process, focusing on the Urgency Index as the target variable. It featured four graphs: one showcasing variable influence (up left) with the number of accidents emerging as the most influential variable, the second graph (up right) assessed model performance across different metrics, the third graph (bottom left) highlighted variable contributions to the Urgency Index with "view blocking objects" having the most significant impact and the fourth (bottom right) highlighted how specific variable values increment the Urgency Index from its mean value, with the presence of trees along streets having the most pronounced effect. Overall, the dashboard offered concise visualisations to understand how different factors influence policy outcomes.



5. Conclusions

The implementation of the AI into the policy making process serves as a transformative shift in governance, focusing on transparency, efficiency and citizen-centric approaches. By utilizing AI tools, policymakers can improve data-driven decision-making, predict future trends, develop, implement and evaluate policies in a more efficient and transparent way.
However, achieving transparency and ensuring that the local governments fully understand the appropriate use of AI, while reducing biases resulting from data, require careful attention.
Transparency can be achieved by integrating XAI techniques to explain AI model decisions and operations in a way that is understandable by humans. This promotes understanding and public trust, which are essential for acceptance and accountability.
Equally important, policymakers need to explain the importance and potential effects of AI systems in a way that is understandable to all parties involved. This involves avoiding technical terms and providing concrete examples to support outcomes.
Moreover, from a data privacy perspective, transparency is about empowering individuals with control over their data. It involves clear communication about the data collection, usage and purpose, allowing people to make informed decisions and protect their privacy rights. For that purpose, local governments should prioritize data integrity and thoroughly evaluate the accuracy, completeness, and representativeness of data before building their use cases. To reduce data biases clear protocols for data collection and sharing should be established alongside ongoing monitoring and evaluation.
Policymakers should also be aware of the shortcomings of AI models and the possibility of bias, highlighting the significance of inclusive and diverse data sources as well as thorough model review.
Furthermore, as outlined in the relevant section above, municipalities should develop and adhere to ethical guidelines and standards for the responsible use of AI in policymaking.
Finally, municipalities should invest time and effort into implementing co-creation processes, to ensure transparency and relevance of their policies, fostering a collaborative environment that benefits all parties involved.
All in all, the collaborative framework outlined promotes stakeholder involvement, capacity building and ethical considerations. It lays the foundation for efficient, accountable and transparent data-driven and AI-based governance, empowering municipalities to address societal challenges and foster public trust.
The aforedescribed pilot case studies, as those were carried out within the AI4PublicPolicy project, outline how the data-driven CRISP-DM methodology was deployed for a novel approach to policy-making process while taking into account the themes addressed within the present paper. Based on their unique scope and objectives, each pilot drafted use cases that drove the pilot deployment of VPME AI-based tools and solutions. The aggregated data were scrutinized and then utilized by the VPME components in order to provide pilot teams with insights, visualisations and reports related to the pilot policies' scope. The procedures presented in the current paper constitute an example framework valuable for public authorities that seek to leverage AI capacities to foster a integrated evidence-based approach to decision and policy making.

Acknowledgements

The current paper is conducted in the context of AI4PublicPolicy. The project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement, No. 101004480.

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