Ethical Artificial Intelligence in the European Union Context: Visualization for Policymaking and Decision Processes

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Abstract - **Based on its success with the standardized Global System for Mobile Communications (GSM) telephony in the 1990s and the General Data Protection Regulation (GDPR) in the 2010s, the European Union (EU) is putting a lot of effort in regulating Artificial Intelligence (AI) and its widespread usage. A term of ethical AI has emerged, and numerous national, European and global guidelines have recently been published, in the hope of creating a unified framework set to be used and implemented across EU and the globe.**

However, a highly convoluted nature of legislative procedures regarding emerging technologies makes it increasingly complicated to map out ethical AI properties and guidelines. Hence, a holistic and data-driven approach towards AI policy-making is proposed. In order to help EU policymakers and lawmakers, ethical AI principles of explainability and autonomy will be contextualized and visualized. Data contextualization is achieved using secondary datasets based on the systematic literature review, while data visualization is implemented in a form of a compact digital dashboard, using Python programming language and its associated visualization libraries.

Goal of the suggested comprehensive solution is to simplify and streamline future decision processes regarding AI topics exclusively from policymakers' perspective. This will indeed shape Europe's digital future and foster trustworthy strategic leadership regarding AI technologies, which is likely to make EU lead by example and become a globally adopted practice.

Keywords - Ethical Artificial Intelligence, European Union, Trustworthy Machine Learning, Explainability, Autonomy, Data Visualization

I. INTRODUCTION

Recent advances of Artificial Intelligence (AI) made this research area popular once again, but it also brought into spotlight some recurring discussions regarding its risks and liabilities. Despite having known about intelligent systems since the early 50's by the likes of Vannevar Bush, John McCarthy and Alan Turing [1], [2], we still have not reached a consensus regarding its definition on which experts would agree upon. One popular definition states that it is "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." [3] In addition, the authors also explain contemporary evolution of AI systems throughout the decades using the metaphor of the "Four Seasons of AI" [4]. After a period of winter in the 80's and 90's, where development seemed slow and enthusiasm low, we have recently entered a period of AI fall. This is a period during which we prepare for a "harvest of the fruits of past statistical advances" that, together with the computational power available nowadays, artificial neural networks and deep learning models is made possible.

When it comes to European policymakers - definition and development of AI is described through a set of strategic documents. In that sense, EU can be considered a front-runner in establishing a framework on ethical rules, guidelines for AI and a just AI transition. European Commission states that "artificial intelligence has become an area of strategic importance and a key driver of economic development. It can bring solutions to many societal challenges. However, socio-economic, legal and ethical impacts have to be carefully addressed." [5] Not only that but the Confederation of European Business Director General Markus J. Beyrer concludes how "the global innovation race intensifies and this is why Europe needs to scale up its innovation policy in the next five years" [6]. In this regard - AI combines emerging technologies, innovative potential and socio-economic disruptions, which urges for a better understanding, risk mitigation and regulation. A definition of AI, as proposed within the European Commission's Communication on AI, describes it as a "systems that displays intelligent behavior by analyzing its environment and taking actions – with some degree of autonomy – to achieve specific goals." [7]

In order to understand better how EU strategic documents have progressed over time, it is best to lay out a short timeline of events corresponding to its key publications. The European Parliament called on the European Commission to assess the impact of AI and made a list of recommendations on civil law rules on robotics [8]. The Parliament drafted a code of ethics for robotics engineers and suggested creating a European agency for robotics and AI, tasked with providing the technical, ethical, and regulatory expertise needed in an AI-driven environment.

In the beginning of 2018, the European Commission adopted a communication to promote the development of AI in Europe, and published a coordinated plan on AI, endorsed by the Council of the European Union, to coordinate the EU Member States' national AI strategies [7].

By the end of 2018 the High-Level Expert Group on Artificial Intelligence (AI HLEG) was established, which was tasked with preparing AI ethics guidelines, drafting AI policies and investment details. Soon after, in April 2019, the Commission published a set of non-binding Ethics guidelines for trustworthy AI [9].

Most recently, European Commission published a white paper on AI discussing how AI ecosystem reflects on citizens, businesses, and services of public interest [10]. In addition to that, the Commission proposed the first legal framework on AI, which addresses the risks of AI and positions Europe to play a leading role globally [11].

II. ETHICAL AI PRINCIPLES

The key EU requirements for achieving trustworthy AI are human agency and oversight, robustness and safety, privacy and data governance, transparency, diversity, non-discrimination and fairness, societal and environmental well-being, accountability. Respect for human autonomy and fundamental rights is at the heart of the seven EU ethical rules. More specifically, autonomy as an ethical AI principle mainly covers the level of human oversight over AI systems by ensuring human agency. What the White Paper on AI [10] revealed was that requirements regarding transparency, traceability and human oversight were not specifically covered under current legislation in many economic sectors. It's not just the EU institutions, several prominent ethical AI researchers argue about the importance of ethical principles and their implementation. Floridi identifies an overarching framework consisting of five core principles for ethical AI: beneficence, non-maleficence, autonomy, justice, and explicability [12]. On the other hand, Gebru focuses on sustainable development goals (SDGs), and environmental impact, financial aspect of pre-training activities, inclusion, and diversity [13]. Many researchers are keen on introducing Explainable AI (XAI) as a means to safeguard transparency and accountability. Some of them are even going a step further with the concept of explicability, which relates to the manner in which the system is transparent, understandable and fair in order to be viewed as being trustworthy [14]. However, one could argue that trustworthy systems are not necessarily ethical, while vice versa ethical systems must be trustworthy, hence making such method of clustering different ethical AI principles non-beneficial. Rather, a more refined way of choosing a number of different aspects as defined by the EU could be more favorable. In terms of bias and fairness, many aspects could be quantified with a various degree of success. What researchers have done so far is to isolate certain diversity and inclusion metrics in order to demonstrate how data possibly discriminates within specific subgroups [15]. This all leads to the proposed research question in this very paper: how main ethical AI principles (explainability and autonomy) can be contextualized and visualized in order to provide better decision processes for AI policymakers.

III. EXPLAINABILITY AND AUTONOMY

Two major ethical AI principles (namely explainability and autonomy) were selected among many ither based on their quantity of scientific publications, number of mentions in different national and supranational documents, as well as their policy impacts as evident in major EU documents on ethical AI.

A. Explainability

An ethical principle of explainability (explicability) will be analyzed as an example of a methodology to be introduced further on in this paper, accompanied by the literature review on explainability tools.

AI Tools and systems are highly complex and opaque, which obfuscates their interpretability. Literature often refers to this as 'black box' systems or models, which can become difficult to interpret [16]. Being interpretable or having interpretable models means that humans can readily understand the reasoning behind predictions and decisions made by those same models. This is slightly different from explainability because interpretability covers only those models that can be easily interpreted such as such as linear regression and decision tree models. Also, it explicitly focuses on models and neglects other aspects of AI such as data and input streams. Another drawback is that interpretability in a nutshell means different things to different parties involved such as data scientists, businessmen, regulators, and user among others. Nevertheless, it is an important segment when it is utilized together with explainability and explicability. For example, the black box model could be a decision tree algorithm uncovering this simple interpretable model. By adding the data flow and output reasoning, the whole system becomes explicit and explainable. Of course, an example in question is quite simple so no elaborate visualizations or communication methods are necessary (other than possibly adding a short remark of how to "read" decision trees) for it to be understandable by anyone.

The opaque nature of algorithms and the perceived unfairness and discrimination experienced [17] have ensured that there has been an outcry for more insight into the inner workings of machine learning models. One example of a model that has received exhaustive scientific attention is the COMPAS algorithm for recidivism [18]. This is an example of a model which brough forth further scrutiny of the impact these algorithms might have. Calls for transparency and accountability have contributed to a renewed interest in the possibilities of Explainable Artificial Intelligence (XAI).

B. Autonomy

Ever since the Third Industrial Revolution, there has been an increase autonomy of intelligent systems: machines and robots alike. This offered new opportunities but also some unwanted impacts on the society at large. When talking about autonomy, there is an inherent and overarching relationship between humans and machines, also the need of "the effective human systems integration that must result for trust in these new systems and their applications to increase and to be sustained" [21]. Therefore, "human oversight is advocated as a solution against the risks of increasing reliance on algorithmic tools" [22] as important concept of "the human in the loop" guarantees to mitigate possible dangers to human autonomy due to lack of transparency and opaque algorithmic models.

When talking about autonomy, which is a term borrowed from moral philosophy, responsible AI literature talks about two types of autonomies: human autonomy and machine autonomy. Although many would assume that because of autonomous AI systems (such as cars), autonomy on itself would automatically imply machine autonomy, in the context of trustworthy and ethical AI – it is rather the human autonomy being put front and center (unless stated otherwise) [23]. Nevertheless, in the recent literature authors usually focus on machine autonomy in order to arrive to a necessity of human oversight as one of the criteria for ethical AI systems.

Depending on the AI system, a number of autonomy degrees have been theorized and established. For example, in the case of autonomous vehicles, SAE (Society of Automotive Engineers) US association defined in 2018 six levels of automation and its corresponding human oversight ratio:

0) No driving automation

1) Driver assistance

2) Partial driving automation

3) Conditional driving automation

4) High driving automation

5) Full driving automation

Apart from driving, other areas have not fully explored the concept of autonomy but it is a work in progress, while some others (industrial and plant automation) have adopted the same approach as SAE suggested. For instance, in the field of education AI (EdAI), a term of Augmented Intelligence (AuI) or Intelligence Augmentation (IA) is mentioned as a much more holistic system, which takes human autonomy and decisions into account, as it can cater for the perspectives of service system designers, human-computer interaction designers and other related areas that focus more on an integration between the humans and machines. In the field of robotics and cybernetics, authors often refer to LORA or Levels of Robot Autonomy, but level-based system varies in different papers. In the paper by Beer et al. [24] authors suggest taxonomy levels rather than numerical based levels. They propose these ten degrees: manual, tele-operation, batch processing, decision support, shared control with human initiative, shared control with robot initiative, executive control, supervisory control, and full autonomy. They also argue that while autonomy may be considered along a continuum (e.g., 0-100), conceptualizing specific degrees of autonomy is difficult.

IV. DATA VISUALIZATION

Following the best practices of quantitative methods and numerical analysis, datasets necessary for the visualization purposes will obtained from open data access portals (such as Data.Europe). Data transformation and visualization operations are implemented using Python programming language and Jupyter Notebook interface, while libraries used will range from Matplotlib for plotting graphs – to Plotly and Dash for creating an interactive visualization dashboard.

A. Methodology

Methodology relating to visualizing ethical AI principles will be based on a comprehensive theoretical background of data-driven policymaking, data visualization and knowledge representation in general.

Data-driven or evidence-based policymaking tends to nurture real-time policy adoption based on data, creating supra-national regulatory frameworks, bringing together both data experts and legal, policy experts. However, it is important to distinguish between the policy on AI and policy with AI. This research focuses on the former and utilizing exploratory data analysis and visualization methods to illustrate how current AI policies can be viewed within the context of ethical guidelines and principles. Information visualization and visual analytics are defined as "the use of computer-supported interactive, visual representations of abstract data to amplify cognition." [25] By living in the current age of big data, where the growing amount of data can contain hidden knowledge, those information sources should be considered in decision-making.

In order to bridge the gap between different parties, science-policy interfaces with interactive visualization capabilities are deemed necessary [26]. AI ethics education initiatives fostering AI literacy use a variety of interdisciplinary strategies to communicate key ethical concepts, including creating so called ethical matrices to consider values of different stakeholders in technology, imagining future AI and its implications, reflecting on AI representations in popular media and the news, discussing and debating key ethical questions, and engaging in programming activities that spur learners to critically examine algorithms and bias [27]. This is completely in line with the EU assessment list on ethical AI as defined within the AI HLEG Sectoral considerations for Trustworthy AI.

Contextualization items will be an association between six different thematic subdomains based on the paper by Righi et al. [28] , where authors identify these thematic knowledge subdomains in AI:

- Speech recognition, natural language processing (NLP) and synthesis
- Face and image recognition
- Connected and automated vehicles
- Automation processes and robotics
- Theoretical methods
- Platform as a Service (PaaS) and Software as a Service

The purpose of having subdomains is to have a constant logical connection between explainability and autonomy despite having completely different visualization methods, with latter being the result of the inherent difference and dimension within the principles themselves.

B. Explainability

Visualizing explainability has a goal of demystifying the black box of AI based on its inputs (data), internal mechanics (algorithms) and outputs (predictions). The purpose is to create information visualization or an infographic that will be simple and understandable to policymakers and government officials, showing all important specification of the AI system: subdomain, risk assessment, data specifications and more. Scientific community recommends using CPR (Critical Path Method), PERT (Program Evaluation Review Technique) charts or diagrams when encountering complex processes and graphs that need to be simplified [29]. They are used extensively as a project and product managing tools.

Explainability in terms of visualization was devised as a combination of explainable data (input), prediction (output) and algorithms (black box of machine learning models). In addition, explainability cannot be isolated and it was necessary to provide additional information that would give policymakers both contextualization and meaningful connection to other ethical AI principles. This overarching connection can be achieved through: AI technical subdomain, "traffic light" style of risk assessment, and information on personal data usage through protection principles established in existing EU documents.Therefore, simple infographics and PERT charts are used as a visualization method to explain convoluted machine learning methods as a solution for the ethical AI principle of explainability. An example of a generic Covid-19 (SARS-CoV-2) contact tracing AI-based application solution will be visualized and explained as a result and findings regarding explainability. For this purpose, a paper on such a method will be taken as a demonstrative use case [30]. Figure 1 explains how full system explainability for policymakers can be achieved in such a way that they are not required to know technical details of the machine learning model used.

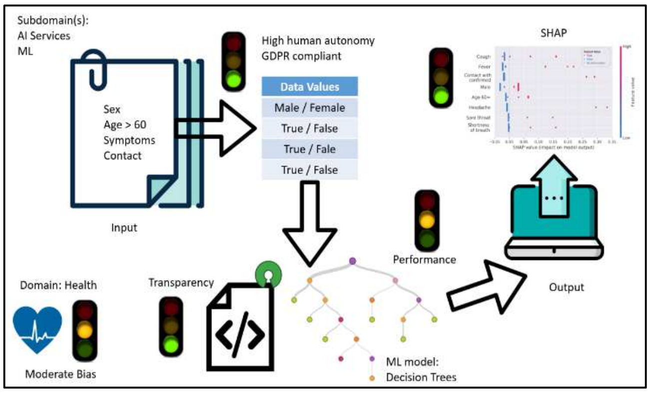

Figure 1 - Full system explainability based on the COVID-19 contract tracing machine learning model application

Design of explainability infographics were inspired by the concept learning flash cards used for learning complex subjects. As evident, the focus is not just on input (patient data), algorithm (decision trees) and output (cumulative general statistics). In addition, it is explained how data is translated into machine readable structure and how output is viewed to the experts. In this case, explainability for output also utilizes SHAP or Shapley value, mentioned in other research papers, which often take into account only a small portion of the whole system, while the bigger picture is often obfuscated and unclear. Not only does this approach shed light about the entire systems' explainability but it also signalizes risk involved in various machine learning system stages. Also, both main domains and subdomains are clearly stated. Risk is depicted using a traffic light-based notification system and we can see that medium risk is due to the domain of health, which often deals with sensitive data and harmful generalizations. Another medium risk is identified in using decision trees, which often perform very fast and do not use a lot of computing power but are prone to overfitting and gives have a lower prediction accuracy for a dataset compared to other machine learning algorithms. In turn, information gain in a decision tree with categorical variables gives a biased response. Using infographics as presented here, policymakers will be able to go through more use-cases – both faster and with greater understanding.

C. Autonomy

Autonomy is viewed through the lens of human autonomy (and oversight) and it is represented by the obtained data on Techno-economic segment of AI available via data.europe.eu as a CSV (Comma Separated Value) dataset. Human autonomy can be therefore contextualized through individual EU projects, and each based on their unique geographical area (country code), six distinct AI subdomain (AI services, Computer vision, Connected and Automated vehicles, Machine learning, Natural language processing, Robotics and Automation), Revealed Competitive Advantage (RCA) and a world share. RCA index is defined as a relative advantage of a country in a certain class of goods or services. Timespan of the available dataset is from 2008 until 2018.

In order to visualize human oversight risk assessment, an assumption is made based on risk levels defined by the EU Proposal for a Regulation Laying down Harmonised Rules on Artificial Intelligence [11], which states that different AI subdomains (or areas to be specific) can be given either a contextual or point based system based on the level of human agency and risk involved. Therefore, this research is establishing a decimal system between zero and one. Zero value means that it is a completely autonomous system with great risks as no oversight is possible, and one being completely human controlled. Everything else must fall into category between those two values, which is an assumption made so that it can make data visualization possible based on a quantifiable value. This is necessary as concrete values need to be associated by the values data visualization axis. Since the dataset in question is multidimensional (geographic area, AU subdomain, RCA, world share), this is an excellent opportunity to create a multidimensional visualization.

Because RCA and the world share indicators are inherently tied together to each other on a macroeconomic basis, an attempt of adding a secondary set to replace the world share is considered. Moreover, an additional data could be added in order to represent social and human-centered related AI values which could provide more diverse indicators. Therefore, a dataset on public attitude towards AI is proposed as a future addition to this research.

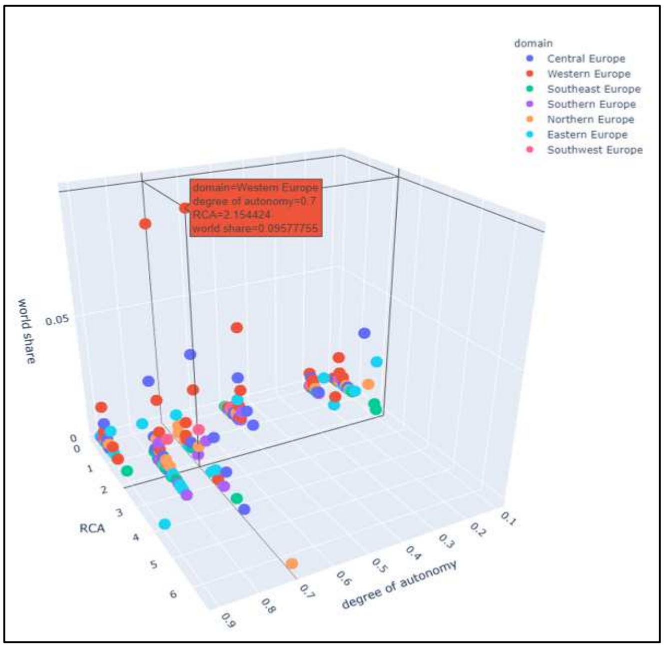

Figure 2 - Interactive 3D visualization of human autonomy levels of EU AI projects in relation to other variables

Since autonomy datasets were prepared as multidimensional, it is usually the best approach to turn to 3D spatial data visualization across different variables and domains. Visualization results can be observed in Figure 2.

Each project was associated to a certain European country which resulted in too many degrees of freedom for that variable. Instead, all countries were grouped into European regions (Central, Western, Southeast, Southern, Northern, Eastern and Southwest) because with seven distinct data point colors, it is possible to easily read the information from this type of visualization. Degree of autonomy was assumed based on the AI subdomain of each project. Due to certain limitations, both RCA and world share were kept as valid dimensions in this visualization iteration, however world share should be replaced by an aggregated dataset on public attitude towards AI in order to include social dimension in addition to economic ones. This visualization shows that the most financially successful AI projects in Europe (corresponding to high RCA and/or world share) are the ones located in Central and Western Europe. Also, they are usually highly automated (high machine autonomy but low human autonomy), which might be a sign for concern as human agency might be neglected. Interactive capabilities include scaling and rotation of the cube, with each data point clickable to obtain detailed information.

V. Conclusion

Based on the preliminary results and exploratory data visualizations of two main ethical AI principles, it is evident how AI subdomains and its inherent generalizations are incorrectly driving the analysis of such datasets towards some incoherencies that could result in inefficient AI policies. Instead, specific use-cases and AI-services should be examined before evaluating the associated risk scores related to autonomy and human agency. It is clear how such joint datasets do not exist on the EU level despite being a crucial prerequisite in creating supranational policies. Additionally, when assessing autonomy levels through the viewpoint of multidimensional data entries, an aggregation of additional datasets such as the attitude of people towards AI should be strongly considered. Both algorithmic structures and bias found within are replicated based on social structures and depending on how data was acquired at an individual level. Therefore, EU segmentation is visible in visualization results as well, based on different geographic regions due to country-specific attributes of heterogeneity, industrial development, language, population statistics, culture, and others. To conclude, it is necessary to test explainability models with policymakers and communicate with them the shortcomings of contextualizing, as well as visualizing other ethical AI principles (namely autonomy) using proper datasets on both nationwide and European level.

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