Responsible AI in Healthcare*
Overview of the Research Activities carried out at the Department of Informatics, Systems, and Communication of the University of Milano-Bicocca, within the CINI National Laboratory “Artificial Intelligence and Intelligent Systems” (AIIS)†

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Abstract
This article discusses open problems, implemented solutions, and future research in the area of responsible AI in healthcare. In particular, we illustrate two main research themes related to the work of two laboratories within the Department of Informatics, Systems, and Communication at the University of Milano-Bicocca. The problems addressed concern, in particular, uncertainty in medical data and machine advice, and the problem of online health information disorder.

1 Research Themes
According to the Ethics Guidelines for Trustworthy Artificial Intelligence (AI) [AA.VV., 2021], a document defined by the High-Level Expert Group on Artificial Intelligence (AI HLEG) set up by the European Commission, seven are the key requirements that AI systems should meet in order to be trustworthy:

1. **Human agency and oversight**, i.e., supporting human autonomy and decision-making, as prescribed by the principle of respect for human autonomy;
2. **Technical robustness and safety**, i.e., including resilience to attack and security, fall back plan and general safety, accuracy, reliability and reproducibility;
3. **Privacy and data governance**, i.e., including respect for privacy, quality and integrity of data, and access to data;
4. **Transparency**, i.e., including traceability, explainability and communication;
5. **Diversity, non-discrimination and fairness**, i.e., including the avoidance of unfair bias, accessibility and universal design, and stakeholder participation;
6. **Societal and environmental well-being**, i.e., including sustainability and environmental friendliness, social impact, society and democracy;
7. **Accountability**, i.e., including auditability, minimisation and reporting of negative impact, trade-offs and redress.

The researchers of the Department of Informatics, Systems and Communication (DISCo) of the University of Milano-Bicocca, who work on the macro theme of the article, are organized in different research laboratories active on two main research themes, addressing some of the key requirements illustrated before in the health domain. In particular, Federico Cabitza and Davide Ciucci, members of the Modeling Uncertainty, Decisions and Interaction Laboratory (MUDILAB), discuss the problem of uncertainty in data that feed machine learning algorithms and the importance of the cooperation between AI and human decision-makers in healthcare. All the seven key requirements are involved, with particular reference to 1, 4, and 6. Gabriella Pasi and Marco Viviani, members of the Information and Knowledge Representation, Retrieval and Reasoning Laboratory (IKR3 LAB), address the problem of health information disorder and discuss several open issues and research directions related mainly to key requirements 1, 2, 4, 5, and 6.

2 Responsible AI as a Support for Healthcare Decisions (F. Cabitza and D. Ciucci)
In this section, we address some responsibility and trustworthiness issues in current machine learning algorithms and decision support systems in healthcare. First of all, medical data can be affected by different types of uncertainty/variability,
some of which are not usually accounted for when developing ML models. In particular, we refer to different forms of variability:

- **Biological variability**, which occurs when a person is associated with more or less different values that express a health condition over time;
- **Analytical variability**, which occurs when a testing equipment, although calibrated, produces different values for a specific patient/subject with respect to other equipment (from the same vendor or different vendors);
- **Pre- and post-analytical variability**, which occurs when different values in the same exam for the same subject can be due to different ways (including erroneous ones) to use the equipment or produce data about test results.

These sources of variability add on to the noise due to more common (and treated) sources of data or label noise [Cabitza and Batini, 2016; Cabitza et al., 2019a; Cabitza et al., 2019b; Hüllermeier and Waegeman, 2021]:

- **Missing data**, in different forms, e.g., a value that is not known or a patient that does not reveal a symptom;
- **Vagueness**, such as a symptom is mild rather than severe;
- A physician undecided on the interpretation of an exam, perhaps with a degree of confidence;
- **Noise**, in instruments or in reporting data.

In light of these considerations, it is important to get awareness of potential sources of noise in biological and clinical data and conceive novel methods to both mitigate their impact and manage the related variability and uncertainty.

To this aim, we are developing a set of new algorithms able to cope with all these flaws in healthcare data. We explore different approaches: partially labeled data [Campagner et al., 2020], superset learning [Campagner et al., 2021b], multi-rater annotation [Campagner et al., 2021c], cautious learning [Campagner et al., 2021a], and soft clustering [Campagner and Ciucci, 2019]. The goal is to create a framework for robustness validation of classification systems based on Machine Learning. The developed tools and algorithms should be able to handle different forms of uncertainty simultaneously and to abstain from giving a precise answer whenever this is not possible or too risky.

Moreover, we advocate the need to move beyond aggregation methods by mere majority voting in ground truthing [Campagner et al., 2021a], that is the production of the ground truth labels to be used in supervised learning, as this could result in excessive simplification with respect to the complexity of the phenomenon at hand, for which multiple right and complementary interpretations are possible to coexist for a single case [Basile et al., 2021].

Finally, we also advocate further research on the design and evaluation of alternative interaction protocols [Cabitza et al., 2021] stipulating how human decision makers could use, and in some case even collaborate, with AI-based decision support systems, in order to mitigate the risk of having cognitive biases, like automation bias, automation complacency, AI over-reliance and its opposite, the prejudice against the machine [Cabitza, 2019], which undermine the effectiveness and efficiency of computer-supported decision making process. This will lead to more reliable and trustworthy decision support systems.

### 3 Responsible AI and Health Information Disorder (G. Pasi and M. Viviani)

In this section we address the issue of the responsibility and trustworthiness of AI algorithms in the context of the spread of different forms of health-related communication pollution. This is an important issue, which is fundamental to both understand and limit the generation and diffusion of rumors, misinformation, and disinformation [Guess and Lyons, 2020; Wardle et al., 2018], especially in the health domain [Di Sotto and Viviani, 2022; Swire-Thompson and Lazer, 2019; Viviani and Pasi, 2017]. All these forms of false, unreliable, low-quality information, generated with or without fraudulent intent, have recently been grouped under the name of information disorder [Wardle and Derakhshan, 2017].

#### 3.1 Health Information Disorder Generation

A first aspect that needs to be addressed in this context is that there are several systems based on AI techniques that have allowed in recent years: (i) the generation of increasingly realistic fraudulent content, and (ii) the large-scale dissemination of the same, often, with manipulative intent [Bontridder and Poullet, 2021]. As far as the first aspect is concerned, let us think, for example, to the phenomenon of deep fakes [Hancock and Bailenson, 2021]; as far as the second aspect is concerned, we may cite the increasing effectiveness of the systems of micro-targeting [Zuiderveen Borgesius et al., 2018], of information filtering [Chitra and Musco, 2020], and of social bot generation [Allem and Ferrara, 2018].

The ethical implications of information disorder generation essentially concern human dignity, autonomy, and democracy [Bæøe et al., 2020; Bontridder and Poullet, 2021]. Human dignity, because people are treated not as persons but as “temporary aggregates of data processed at industrial scale” [AA.VV., 2021], often with opinion manipulation intents, leaving to people the impression that they are receiving the same information as any other person in the digital ecosystem when in fact they are part of filter bubbles [Holone, 2016]. This problem is closely related to that of autonomy, in fact users are not completely able to build their own (digital) identity. Finally, manipulation leading to excessive polarization (as seen above) produces impossibility to make globally shared decisions, leading to serious repercussions in several areas of well-being, not least health.

In this area, we are working on the definition of models and methodologies based on graph mining and NLP techniques for the identification of echo chambers and limiting the problem of their formation, which is closely related to the problem of selective filtering of information, including with respect to the health domain [Villa et al., 2021].

#### 3.2 Health Information Disorder Detection

Due to the spread of online information disorder, a second aspect that needs to be addressed is to identify different forms
of communication pollution in different media formats, including in the health domain; in this context several solutions have been proposed in recent years [Cui et al., 2020; Dharawat et al., 2020; Hou et al., 2019; Upadhyay et al., 2021; Zhao et al., 2021].

Ethical issues that arise in this area concern the fact that the algorithms developed to identify information disorder should not impede freedom of expression and autonomy in decision making. According to [Brachman and Schmolze, 1985], “permitting AI systems to regulate content automatically would [...] seriously affect freedom of expression and information”. This, in particular, because “it is not clear how often and under which circumstances ex ante filtering or blocking take place” [Marsden and Meyer, 2019], and because AI systems trained to detect information disorder could produce false positives and false negatives. Indeed, such systems “could lead to over-censorship of legitimate content that is machine-labeled incorrectly as disinformation” [Marsden and Meyer, 2019]. Such problems, related to a non-transparent or incorrect identification or filtering of information judged as not genuine, brings with it the problems related to awareness, and therefore autonomy, in decisions.

Therefore, in the development of solutions for the identification of information disorder (also related to health information), we are currently investigating models and methodologies that allow users not to have a hard filter with respect to access to information (based on their genuineness estimated by the system). In fact, we are evaluating the possibility of providing users with a ranking of the information that takes into account a gradual notion of genuineness [Goeuriot et al., 2021a; Putri et al., 2021], instead of a binary notion as done so far in the literature.

Other issues concern: (i) data collection and data processing, since they can be carried out incorrectly, or on data that already contain bias, or are incomplete with respect to different cultural environments (e.g., based on the use of a single language); (ii) the presence of opacity in algorithms with respect to not obvious connections between the data used, how they were used, and the obtained conclusions, which, in addition, can only be as reliable as the data they are based on. Such issues lead to the so-called inscrutable evidence and misguided evidence, as reported in [Trocin et al., 2021].

To take these issues into consideration, we have recently worked on the definition suitable labeled datasets and evaluation strategies within the CLEF eHealth Evaluation Lab [Goeuriot et al., 2021a], which focuses on the Consumer Health Search (CHS) task [Goeuriot et al., 2021b]. In addition, we have been working on the development of model-driven solutions for the evaluation of the genuineness of information (including health information), which are based on the use of Multi-Criteria Decision Making (MCDM) techniques where the system proves to be explainable with respect to the results obtained [Pasi et al., 2019].

4 Funded Research Projects

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