Artificial intelligence and medical imaging
2018: French Radiology Community white paper

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Abstract The rapid development of information technology and data processing capabilities has led to the creation of new tools known as artificial intelligence (AI). Medical applications of AI are emerging, and the French radiology community felt it was therefore timely to issue a position paper on AI as part of its role as a leader in the development of digital projects. Essential information about the application of AI to radiology includes a description of the available algorithms with a glossary; a review of the issues raised by healthcare data, notably those pertaining to imaging (imaging data and co-variables, metadata); a look at research and innovation; an overview of current and future applications; a discussion of AI education; and a scrutiny of ethical issues. In addition to the principles set forth at the Asilomar Conference on Beneficial AI, the French radiology community has developed ten principles aimed at governing the use and development of AI tools in a manner that will create a concerted approach centered on benefits to patients, while also ensuring good integration within clinical workflows. High-quality care in radiology and opportunities for managing large datasets are two avenues relevant to the development of a precision, personalized, and participative radiology practice characterized by improved predictive and preventive capabilities.

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Artificial intelligence (AI) is growing exponentially in many sectors. Common applications of AI include voice-powered personal assistants, behavioral algorithms applied to real-time telephone conversations, and purchasing recommendations driven by predictive analytics. This progression of AI is resulting in disruptive innovations of which some examples are voice recognition, automatic translation, self-driving cars, face recognition, military and civilian robotics, and pattern recognition in medical imaging.

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In the field of healthcare, many AI applications are available or under development. The introduction of AI into medical practice is expected to have major consequences for both patients and physicians. The central position of radiology in the healthcare pathway, combined with digitization and the advent of Picture Archiving and Communication Systems (PACSs), has led to the exponential growth of stored digital imaging datasets over the last two decades. Applying AI algorithms to these datasets can optimize the relevance and quality of healthcare and improve the efficiency and accessibility of the healthcare system.

As clinicians who have specialized in diagnostic and therapeutic medical imaging, radiologists must conduct the clinical validation of these data-driven systems and shape their implementation, with the goals of improving patient care and ensuring active surveillance [1–4].

In October 2017, the French Radiology Society (Société française de radiologie) set up an AI task force whose mandate is to reflect on the impact of introducing and implementing AI in the field of medical imaging, with attention to ethical, research, and regulatory issues. The task force worked with the French College of Radiology Teachers (Collège des enseignants en radiologie de France [CERF]) to develop this position paper, which will be updated regularly to ensure that the radiology community stands on the leading edge of deliberations about the use of AI in medical imaging in France. Radiologists will thus guide the integration of these new technologies and measure their impact on their clinical workflow and roles as specialists, with the goal of providing patients with precise, personalized, participative, humane, and high-quality healthcare. This position paper was developed by members of several radiology sub-specialties and by experts in other disciplines such as imaging informatics, engineering, biophysics, and research.

The objectives of this position paper are as follows: (i) to review AI terminology and principles; (ii) to describe regulatory principles and issues raised by datasets composed of images and their co-variables (relevance of imaging study requests, condition of the patient, reporting, follow-up, and other information), known as image metadata; (iii) to provide an update on research and innovation in the area of AI; (iv) to discuss current and potential applications of AI in medical imaging; (v) to describe the role for radiologists in providing education about AI; (vi) to review the ethical and societal issues related to AI; (vii) to suggest principles for the use and organization of AI medical imaging. In addition to this paper updating France’s position on the rapidly evolving area of AI in medical imaging, future complementary publications will focus on specific issues such as ownership of healthcare data in radiology, research in medical imaging AI, and possible future applications.

Definitions of terms and introduction to concepts in artificial intelligence (AI)

From AI to deep neural networks

The term "AI" encompasses the sciences and technologies that use machines to imitate, extend, or even improve on human intelligence. AI is closely linked to the development of information technology, cognitive science, statistics, and algorithms. The glossary in Appendix A lists the definitions of the main terms used in this position paper.

Many fields of research have been developed within the sphere of AI. Over the years, periods of strong enthusiasm fuelling intense research activity have alternated with those of waning interest (known as "AI winters"). The term "AI", as used by the media in 2018 with its expected applications in radiology, refers to a specific subfield, namely, machine-learning (Fig. 1). Machine-learning consists of predicting Y (the label or output) based on D (the input) using a function whose parameters are computed during a training phase, then evaluated during a test phase using data different from those used for training. The test phase evaluates the ability of the algorithm to generalize (i.e., the extent to which it has properly learned to perform the intended task). This test phase is important, as it determines whether the algorithm can provide accurate predictions based on new data. Test phase failures are usually due to overfitting, in which the algorithm simply recognizes data it has been exposed to previously (i.e., has learned data by rote but cannot explain the underlying rule that serves to make predictions).

More specifically, machine-learning tasks in radiology now rely on supervised learning. In supervised learning, the algorithm is presented with data (input; here, images) that have already been mapped by hand to the correct labels (output; here, the label to be predicted by AI). The output may be a categorical variable (in classification tasks such as predicting the ACR score of a mammogram) or a continuous variable (in regression tasks, such as predicting brain age on an MRI scan).

This ability to learn allows the machine to perform tasks that would not be feasible if they had to be programmed manually by specifying all the parameters. An example of such tasks is image, sound, or text recognition. Training tasks may be unsupervised, an example being clustering. The best-known clustering method is principal component analysis (PCA), in which patterns based on one or more dimensions are identified within a mass of heterogeneous information, thereby revealing previously concealed characteristics of the data. Although clustering techniques cannot perform as well as human intelligence in the context of medical imaging, they can be helpful, for instance to identify biases in the data used.
Machine-learning allows the automatic performance of tasks essential to medical imaging. Examples include the detection of abnormalities (computer-aided detection, CADe), the characterization of detected abnormalities (computer-aided diagnosis, CADx), and organ segmentation.

A classic example of machine-learning in radiology is the detection of lung nodules using computed tomography (CT). The algorithm is provided with CT images that have been hand-labeled as showing or not showing lung nodules. At each repeat, the algorithm processes the imaging data and predicts whether nodules are present or not. The correct hand-crafted labels are then provided, and the internal parameters of the algorithm are adjusted to maximize performance. The process is then repeated with a new example. Once the algorithm has been exposed to a ‘sufficient’ number of examples, it can predict the correct label for a new image that has not been previously exposed to, for instance, ‘lung nodule, yes 90%/no 10%’. At present, lung nodule detection by AI is associated with a high false-positive rate. Future developments will likely permit AI to predict nodule malignancy [5].

Data enrichment can improve the predictive abilities of AI. For instance, in radiology, accurately labeled images can be used (e.g., manual segmentation of a nodule or use of biopsy results). However, before starting to train an algorithm to recognize a specific type of image, the extremely time-consuming task of collecting and labeling the data must be performed if predictions similar to or better than those provided by humans are to be obtained.

Labeling can be more or less qualitative. For segmentation, for instance, the radiologist must painstakingly delineate the boundaries of the tumor by hand. The correct label, which the AI should predict, is then identified with great accuracy. This is not always the case. Data scientists (specializing in numerical data, statistics, management informatics, and the analysis of big data for corporations) can work with weak labels that are less accurate and less well structured. For instance, although a radiology report contains information that can be categorized as a label (e.g., presence of a nodule in a given lung segment), an intermediate data processing step is needed to associate this label with what is visible in the image. Labels with greater accuracy and structure facilitate the task of the algorithm and decrease the required size of the dataset.

Machine-learning algorithms include a specific category that is currently generating major advances, namely, deep learning or deep neural networks. The term 'deep' refers to the multiplicity of the neural processing layers used in the network.

**Deep learning in medical imaging**

Among learning algorithms, deep neural networks have led to breakthroughs in task performance, notably in the field of medical imaging. Until recently, conventional pattern recognition learning systems were composed of two parts: a hand-programmed feature extractor and a machine-learning algorithm for classifying the image.

A useful example is the automatic characterization of a lung nodule as benign or malignant. The feature extraction phase involves (i) segmenting the nodule; then (ii) selecting and extracting the nodule features that are relevant for discriminating between a benign and a malignant tumor such as the boundaries, density, enhancement, roughness, and entropy. These features are grouped into vectors. In the next phase, the machine-learning algorithm for processing these vectors is selected in order to correctly classify the nodule.

Image segmentation and selection of the relevant features for extraction are extraordinarily complex tasks during which errors can occur. It is virtually impossible to prove that the optimal features for resolving the problem at hand have been selected. Convolutional neural networks are decisive for overcoming this obstacle (Fig. 2), as they radically change the paradigm by combining the two phases, i.e., by both extracting the features and classifying the image. The image features do not need to be extracted first to allow subsequent classification. Deep learning networks use the pixels in the image or a region of the image as input and transform them via multiple processing layers (hence, the adjective 'deep') into the decision or classification (output).

An example is ResNet-50, which has 50 processing layers.

The intermediate, or hidden, layers are responsible for the extraction of image features that have not been explicitly programmed by the network designer but have, instead, been learned by the network via an analysis of the hand-labeled data provided during the training phase. The process is performed end-to-end, from raw data analysis to image classification, with the intermediate steps being conducted by the network.

A detailed explanation of neural network functioning would be outside the scope of this paper. Many online
resources are available [6]. In sum, deep neural networks bear some resemblance to the nervous system, as they consist of interconnected ‘artificial neurons’. Each neuron receives a weighted sum (W, the weight of the function parameters computed by the neuron) of input X and activates its output Y when the sum rises above a predetermined cut-off. The prediction made by the network (output) is compared to the expected prediction. The learning process iteratively modifies the ‘synaptic’ weight W to minimize error, thereby providing a prediction that most closely resembles the expected result.

The term ‘deep’ refers to the organization of the network in multiple layers. The intermediate layers are known as hidden layers. This organization allows non-linear answers to be provided to a question and is known as a multiple layer neural network or deep learning network. Two problems inherent in convolutional neural networks should be pointed out: (i) effective training of these networks requires large amounts of hand-labeled data and (ii), predictions made cannot be readily traced back to the features extracted by the algorithm, a phenomenon known as the black box of deep neural networks.

Medical imaging data: regulation and issues

Regulating data collection (General Data Protection Regulation, French Computerised Data and Freedom Act, French Jardé law)

Because AI research relies on databases, France’s implementation of the European General Data Protection Regulation (GDPR) on 25 May 2018 has further changed the environment within which AI research can develop. In addition, the French Computerized Data and Freedom Act (Loi Informatique et Libertés, which has modernised the healthcare system) has been revised to take data-driven research into account. Finally, French clinical research legislation has been substantially modified over the last 2 years. The Jardé law (whose enactment decree was issued in November 2016 then amended several times) [7] defines a new structure that distinguishes three types of healthcare research studies: studies directly involving human patients, studies of personal healthcare data, and studies of biological samples. Studies of data whose collection and analysis require no interaction with individuals are subject only to the requirements set forth in the French Computerized Data and Freedom Act. These studies can be retrospective or prospective.

Requirement for patient information

The patients must be informed that their data will be used for research purposes. To this end, each patient must receive a written information document to ensure that the patient has no objections to the use of his or her data for the study. The new law allows a global consent process, in which the patient agrees once and for all to the use of his or her data for scientific research purposes only. Until a reference methodology is available for research on personal healthcare data (MR004), the MR003 methodology [7] designed for non-interventional studies can be used. Otherwise, advice should be sought from the French Expert Committee on Research, Studies, and Evaluations in Healthcare (Comité d’expertise pour les recherches, les études et les evaluations dans le domaine de la santé, CEREES) [8]. The committee must provide a reply within 1 month about the methodology, need for data collection, relevance of the collected data, and scientific quality of the project. A request to waive the requirement for patient information can be submitted to the CEREES. Failure of the CEREES to reply within 1 month is equivalent to approval. Authorization should then be sought from the French Data Protection Authority (Commission nationale de l’informatique et des libertés, CNIL). French law does not require ethics committee approval for research on personal healthcare data. This fact can create conflicts with English-language scientific journal editors, who may refuse to publish studies for which ethics committee approval was not obtained. The role for ethics committees in this setting remains to be determined.

Requirement for pseudonymization

The data collected in the database must be de-identified (i.e., pseudonymized). Medical images constitute a specific type of data for which precautions are required. Additionally, pseudonymization issues also arise at the international level. The DICOM format includes information on the image and technique, imaging center, and patient, which can be deleted (Dicom 1 and 2) [9]. De-identification is a more complex and irreversible process that also removes all links between the ‘anonymized’ image and other files such as the protected health information and data-sharing log, which connects a study to a patient. Surface reconstruction of volume acquisitions of the brain and face can provide detailed images of the face of the patient, which may allow re-identification. Such re-identification may be facilitated by the development and generalization of facial recognition techniques [10]. To prevent re-identification, defacing or skull-stripping techniques must be used in multicenter studies of brain or ear, nose, and throat disorders [11].

Responsibilities and undertakings

Beyond the obligations imposed by French and European regulations on clinical research, medical imaging research raises specific ethical and deontological problems. Guidelines for establishing and using databases have been established (Appendix B), both to guarantee the quality of the data and to ensure equity among all those involved in collecting then using the data. Retrospective and prospective studies raise somewhat different problems.

Commitments regarding data relevance and quality

When evaluating the performance of a diagnostic test, it is crucial to define the population the test is intended for [12], particularly in data-driven research, because the negative and positive predictive values of a diagnostic test vary with the prevalence of the disease in the cohort study. This prevalence differs depending on whether the test is used for screening or for primary, secondary, or tertiary care [13]. In addition, the presentation may vary with the stage of the
disease. Radiologists will have a major contribution to make in defining the clinical relevance of the datasets (i.e., ensuring that they accurately reflect the population targeted by the application) and in selecting the reference standard test (e.g., histology or expert radiologist opinion).

Imaging data raise an additional challenge related to the variability in acquisition conditions and to the fast pace of technological improvements (moving target). For a given disease, an imaging study can be performed using a variety of devices (from different manufacturers or with different antennae or software versions, etc.). Acquisition and reconstruction protocols vary also in terms of slice thickness, spatial and temporal resolution, signal and contrast-to-noise ratio, and filters. This variability exists not only across centers, but also over time, as medical imaging techniques are continuously evolving. Radiologists must guarantee the good quality of the results, both upstream from the AI algorithms (selection of a technically relevant dataset) and downstream, to maintain algorithm performance as the technology moves forward. Finally, the requirements of evidence-based medicine should be applied to AI, as they are to other diagnostic tests. Thus, standardized reporting methods should be used for the populations, reference standard tests, and conditions of use. Additionally, studies will have to assess the clinical impact of AI on patient management and outcomes [13]. This clinical evaluation downstream of the registration and marketing of AI algorithms is another crucial area in which radiologists will guarantee the clinical validity of AI tools over time [14].

Commitments regarding equity
The establishment of large databases suitable for AI research will require the involvement of multiple radiology teams, which will contribute to variable degrees. The manner in which the products of the research are distributed among these teams will have to be defined. For prospective studies or the prospective establishment of a database, the study investigators will be aware that a study is being performed. Retrospective studies, in contrast, may include many imaging studies done outside the study healthcare facility and then integrated into its PACS to facilitate image comparisons and patient follow-up. By law, the person or persons who have supplied the human and financial resources in order to establish the database have the right to exploit the database. Nevertheless, with the development of data warehouses that store healthcare data in a structured manner to allow their subsequent use for research, all imaging studies contribute to a database. In addition, PACSs serve as databases when they are searched retrospectively for a research project.

These databases are often associated with metadata including clinical findings, laboratory test results, and other information. Beyond radiologists, the ethical and deontological obligations extend to professionals in other specialties. The development of methods to inform (at the very least) and involve them in the conduct of the research project that is based on data they contributed to collect is probably desirable.

The issue underlying these questions is the equitable sharing of the products of the research. The radiology community should hold discussions on these problems and issue recommendations suggesting solutions.

Research and development

Research in imaging AI rests on the ability to define appropriate questions and research areas, access relevant high quality labeled data, and process these data using suitable mathematical and statistical tools. France exhibits considerable potential in all these domains.

Academic research is vigorous in the field of medical imaging in France. Preclinical and clinical imaging research networks are continuing to develop a robust architecture. In addition, France has a sturdy academic fabric of schools, universities, accredited national research institutes (Inserm, INRIA, CNRS), and researchers in mathematics. These academic resources are interfaced with a burgeoning industrial ecosystem of start-ups, small- and medium-sized businesses, and large corporations involved in medical imaging. A major goal is to promote interconnections among these academic and industrial domains of expertise that focus on avenues for innovation, at both the national and the international levels.

Considerable research assets exist in the fields of medical imaging and AI in France

Recognized medical imaging research groups and facilities

The quality and vitality of medical imaging research in France were underlined in a 2014 report (PIPAME Imagerie du Futur) written under the auspices of the French Ministry for Industry and the General Agency for Competitiveness in Industry and Services (Direction Générale de la Compétitivité de l’Industrie et des Services, DGCI) [19].

Individually, university radiologists in France are deeply involved in research institutions, including their university hospitals and research units (CNRS, Inserm, and topical research laboratories and groups), which they coordinate or with which they are affiliated [16]. Some universities have been granted the IDEX label, which provides access to specific funding. In addition, France Life Imaging (FLI) is a unique national French institution for imaging research whose goal is to federate all those involved in preclinical imaging research. In 2015, the French Radiology Society and the French College of Radiology Teachers, in collaboration with the French College of Nuclear Medicine and French Society for Nuclear Medicine, created the collaborative clinical research network FORCE Imaging.

Much collaborative work is already being performed in the field of AI by university radiologists and mathematicians at universities and other higher education institutions. However, these collaborations are not recorded in a nationwide catalogue and, consequently, do not have the high profile required given the current competitive international environment [17–22].
A recognized high-performing French school of mathematics

Mathematics departments that focus on big data and use deep learning exist within French universities and engineering schools (Polytechnique, École Centrale, École normale supérieure, and many others). Many research and development directors of the GAFA corporations were trained in these institutions. Organizing these places of learning and bringing them together on campuses such as ParisTech will promote exchanges and elevate their international profile.

Start-ups and industries focused on innovation: French Tech

Over 90 start-ups in the field of medical imaging AI are known to exist in France. Competitiveness clusters such as MEDICEN, with the INRIA and SNITEM, support and promote these start-ups. Within MEDICEN, the strategic action domain Imagie has been partnering for the last 3 years with the French Radiology Society and its Innovations group. To connect actors in radiology and the industry (including MEDICEN, INRIA, SNITEM, and the French Chamber of Commerce and Industry), an annual award that recognizes the most innovative start-ups in the field of imaging has been created. Winners of the award receive support, including help with promotional activities, notably during the annual French-speaking Radiology Meeting (Journées francophones de radiologie). Nevertheless, the dearth of funding for start-ups often prevents innovative methods from progressing beyond the proof-of-concept stage.

Nascent research and development interfaces between medical imaging and industrial innovation

Many universities in France have created interfaces under the form of transdisciplinary (radiology and mathematics) innovation cells that liaise with start-ups and the industry to implement collaborative projects. To date, however, no detailed record of these activities and connections exists in the specific field of imaging AI. At the national research level, the FLI may act as a catalyst, particularly in preclinical research. In clinical research, the FORCE Imaging Group, composed of scientific societies and academic organizations involved in imaging, should also contribute to interfacing activities.

Information and communications systems used in healthcare facilities

Imaging studies are now stored in PACSs in both public and private healthcare facilities. Within a PACS, imaging studies are usually linked to the patient’s electronic medical file. Efforts are under way to organize PACSs at the level of territories, regions, and perhaps even the entire country. This expansion remains incomplete, however, due to problems with single patient identifiers, compatibility among systems that include shared medical files, and absence of a national operating system standard, although the specifications developed at the level of the healthcare facilities are often similar.

A specifically French version of institutional determination; the AI Plan

The AI plan announced by president Macron on March 29, 2018 puts forth a national and European strategy in which healthcare is among the top priorities. It involves establishing a nationwide research network composed of four to five main nodes set within a mesh that covers the entire country. This network will allow the integration of locally developed, high-quality projects. It is intended to enhance communication between publicly funded research activities and the industry. However, radiology is not specifically mentioned as an actor in the AI Plan. A policy of wider access to data is currently being debated at the European level. According to this policy, data access would receive public funding, and health data hubs would be created (CNAM, Inserm). This policy would require 1.5 billion Euros over 5 years, including 400 million for calls for projects and 100 million for a disruptive innovation fund.

Main drivers of, and obstacles to, the development of medical imaging AI research in France

Given this favorable environment, the members of the French Radiology Society are eager to intensify their research activities in the field of medical imaging AI. This will require that obstacles be lifted: (1) access to high quality data (data qualification, data anonymisation and deidentification, and data sharing) will be required and (2) resources will be needed to convert French assets into reality (definition of objectives relevant to medical imaging research, structural resources, evolution of research programs and funding, and data ecosystem).

Regarding data sharing, annotations (co-variables) in the margin of images in an entire set of radiology investigations are useful for applying deep learning [23]. However, systematizing these annotations entails additional costs (due to the additional radiologist time needed), and no quality standards exist to date. Consequently, a common informatics framework must be developed to efficiently share AI models, experimental configurations, and training and test data. Regarding software standardization, several learning tools are available in the public domain (e.g., TensorFlow and Microsoft Cognitive Toolkit), but few of them have been sufficiently evaluated using the different image types and algorithms, and none are optimized or ready for clinical use. A consensus must be developed regarding the minimal core set of variables that must be recorded for deep learning, network architecture sharing, and hyperparameters. Finally, servers capable of handling large amounts of data (e.g., Calcul Canada [24]) will be needed.

In addition to data-related difficulties, several obstacles must be lifted to allow the development of clinical and preclinical research programs in medical imaging AI. The fields of research in medical imaging are vast and extend far beyond image interpretation. Fields in which AI-supported research is already under way include patient selection for imaging studies and patient workflow management; image acquisition optimization tools; abnormality detection aids and automatic abnormality detection tools; image interpretation aids; radiologist post-processing.
The four actions of the radiologist workflow

1. Validate the request
   - Relevance
   - Justification
   - Principle
   - History of the disease
   - Allergies
   - Contra-indications
   - Previous exams
   - Information
   - Consent

2. Perform an appropriate study
   - Protocols
   - Acquisiton
   - Injection
   - Reconstruction
   - Liaison with technicians
   - Optimisation
   - Quality
   - Personnalisation according to the findings

3. Interpret the imaging study
   - Quality
   - Answer to the question asked
   - Measurements
   - Classification
   - Comparison
   - Analysis in the light of other data
   - Analysis of all the images
   - Incidentaloma

4. Communicate results and ensure follow-up
   - Report
   - Key images
   - Informing the patient and the referring professionals
   - Comforting the patient
   - Ensuring follow-up
   - Multidisciplinary meetings / department staff meeting

Figure 3. Role for the radiologist in the patient's care pathway (screening, diagnosis, or follow-up) as described in the official radiologist job description. The complexity of the issues will require numerous AI software programs to ensure good coordination, whether the imaging study is scheduled or performed on an emergent basis.

Workflow management aids including tools for quantification, segmentation, and image registration; image quality assessment aids; ionizing radiation exposure reduction; reporting; and automatic data integration. In all these domains in addition to their role as clinical consultants, radiologists are responsible for guaranteeing the quality and relevance of the information, as well as compliance with good practice standards. Thus, radiologists play a pivotal role in the patient care pathway.

The current programs available in France (Programme hospitalier de recherche clinique [PHRC]) and (Programme de recherche médicoéconomique [PRME]) are ill-suited to AI research. On the other hand, the national calls for expressions of interest in selected topics in the field of imaging, directed to industrials and start-ups, constitute a major asset. The SFR MEDICEN innovation award that supports proof-of-concept studies is an example, and such programs must be expanded.

Under the aegis of the National Professional Council in Radiology (Conseil National Professionnel de la Radiologie), radiologists in France have decided to create a nationwide system for centralizing labeled medical image data. This AI ecosystem, whose creation was announced in June 2018, has considerable potential in a broad range of domains including patient care, teaching, and research. Here also, the French Radiology Society must play a central role in allowing the use of high-quality data associated with relevant clinical questions.

Applications and future prospects

AI has many potential applications in medical imaging, due to its capabilities in the image and semantic domains. Consequently, the main challenges faced by AI in radiology are healthcare safety and quality optimization (personalized and participative radiology), workflow optimization (and therefore medical imaging accessibility), and the development of medical imaging for screening and public health (predictive and preventive radiology).

Healthcare safety and quality

AI will benefit all four pillars of radiology work (Fig. 3): (1) validation of the relevance of the imaging study, (2) application of imaging study protocols, (3) analysis and interpretation of the images, (4) and information with advice about further management [25]. However, for each of these steps, specialized software will have to be developed to meet the medical requirements vital to the optimization of organizations and patient care.
Before the imaging study is performed (step 1), the use of AI as a medical decision-making aid will optimize requests for imaging studies (thus ensuring that the studies are relevant) by automatically considering the clinical situation, good practice guidelines, and imaging study specificity. For instance, for a patient with atypical chest pain, AI may suggest exercise testing, coronary CT angiography, cardiac MRI, coronary angiography, or scintigraphy, based on the demographic and clinical data, results of previous investigations, medical history of the patient, and expected diagnostic performance of the investigation in the light of the patient’s characteristics and suspected health condition. Thus, before validation by the radiologist, the investigation most likely to provide the diagnosis in a given patient can be identified. Similarly, AI will eliminate redundancy of investigations by evaluating the entire patient file for previous investigations that are identical or have similar diagnostic performance.

For performing the imaging study (step 2), AI can suggest means of optimizing the acquisition protocol based on an analysis of the patient’s biometric data, circumstances in which the imaging study is obtained, and data acquired during the imaging study (e.g., extraction of anatomic and global density data from the initial scan to optimize the scan volume and mA setting used for the second scan). Expected benefits of AI-driven protocol optimization are include a substantial decrease in ionizing radiation exposure due to optimization of acquisition parameters and duration as well as a decrease in the number of suboptimal imaging studies that must then be repeated. Finally, the better image filtering and de-noising provided by AI should improve image quality.

Immediately after the imaging study (steps 3 and 4), AI can suggest a preliminary analysis of the results (triage function). This analysis may prove particularly useful in emergencies and in teleradiology by immediately alerting the radiologist to the possibility of a severe abnormality, such as a spinal fracture on the CT scan of a traffic accident victim. AI can automatically provide an appropriate reconstruction of the images; for instance, in the example above, that could be a sagittal reconstruction with a bony filter. Similarly, the instantaneous detection of an inci-dentaloma on MRI can lead AI to suggest additional sequences, thus eliminating the need for the patient to come back for a second imaging study. When reading the images, the radiologist using AI to detect and classify the abnormalities (CAD) improves the sensitivity, specificity, and reproducibility of the results via a ‘second reader’ effect. An automatic search by AI for similar cases based on a semantic analysis of the patient’s file and of the images in the PACS will also provide substantial diagnostic assistance, particularly in patients with rare or orphan diseases. In addition, AI will allow an integrative analysis of the various datasets acquired during the imaging study (e.g., MRI sequences and CT spectral maps). Given the overall steep increase in the volume of data produced by each imaging study, the ability of integrative analysis to provide an improved synthetic overview of the contents of the investigation will substantially decrease the time needed for image interpretation. Information by the radiologist of the patient and health-care provider who requested the imaging study (step 4) will thus be optimized and more complete. Information of the patients, organizations, and healthcare providers will allow the development of personalized and participative radiology.

**Workflow optimization**

AI was recently introduced as a workflow management tool in radiology and is expected to rapidly produce substantial improvements. The case orchestration approach can optimize workflow in several ways. First, AI can show the radiologist the full spectrum of data that are useful for interpreting the images via a semantic analysis of the entire patient file (clinical decision support). Any useful information from the patient’s file is displayed automatically and put in the context of the imaging study that is being performed (e.g., date of disease onset, treatments used, nadir). Second, AI can optimize image display based on the radiologist’s usual practice, which is learned automatically by the AI system during the interpretation of previous similar cases (e.g., division of the screen and automatic launching of post-processing software). Third, AI can automatically perform standardized measurements on the images (e.g., RECIST and computation of hepatic or heart ventricle volume), thereby considerably diminishing the time required for interpretation and freeing the radiologist from the need to perform tedious tasks that provide little intellectual added value. Fourth, image pre-screening and launching of appropriate CAD systems can then be performed by the AI system. The application of AI tools before image interpretation is known as image triage, which is based, for instance, on presence or absence of abnormalities. In fact, displaying previous relevant imaging studies for purposes of comparison seems indispensable and is already proposed for the follow-up of patients with chronic conditions. Finally, comparisons with regional or national databases can match a lesion in the individual patient to those in vast patient cohorts in order to better characterize the lesion and its outcome.

**New developments in imaging: screening and public health**

AI will considerably elevate the profile of the radiologist as an actor for public health by increasing the efficiency of screening campaigns involving standardized image analysis (e.g., screening for lung nodules, breast cancer, and tuberculosis) via selection of those patients whose images require a second reading. AI is expected to improve patient phenotyping and knowledge of risk factors for disease in the general population or target populations (e.g., patients with diabetes). Thus, AI will be able to automatically quantify — even in non-dedicated imaging studies — elements such as vascular calcifications (a cardiovascular risk factor), pulmonary emphysema, organ size and density (screening for non-alcoholic steatohepatitis), and bone calcium (osteoporosis). Improvements in the detection of adverse treatment effects during Phase IV studies (post-marketing surveillance) are needed, since radiology, although widely used and nearly indispensable for validating treatment efficacy, is very much underused for assessing adverse events. By establishing unsupervised correlations between the
clinical data and imaging-study data, AI will be able to detect adverse treatment effects. For instance, AI can correlate changes in hepatic density on CT scans with the use of a treatment known to induce hepatic steatosis. By cross-linking information in several databases, AI can provide increased power for detecting correlations between environmental factors and disease development in the population. Thus, patient-specific data (e.g., exposure to toxic agents and diet) can be correlated with quantitative criteria that are automatically extracted from the images. This method will enhance the detection of weak signals in the general population. For instance, the correlation linking asbestos to pleural plaques and mesothelioma would probably have been detected far more easily using AI than the current systems. Thus, AI will allow the development of predictive and preventive radiology for many diseases and patients.

Education centered on training radiologists to use and evaluate technologies involving AI

This section focuses on using and evaluating AI tools, as programming and development issues are discussed in the section on research. Radiologists should do more than use AI: they must employ their expertise to contribute to the evaluation and development of AI tools. To keep our profession at the forefront of AI deployment, rapid changes will have to be introduced into training programs for radiology residents and continuing medical education programs. Radiologists must receive specific training in AI, which should start with a solid foundation of AI education during their residency. The training of radiology technicians is not discussed in this section, although acquiring expertise in the use of new AI-based tools and developing the new professions that may be offered to technicians in collaboration with radiologists will be crucial. This section also does not discuss the training needs of engineers, mathematicians, researchers, designers, or others interested in medical imaging. Meeting these needs is nevertheless of the utmost importance if AI tools beneficial to patients and physicians are to be developed.

Basic principles of the techniques used in AI

Radiologists guarantee these tools, which enhance their knowledge, will be used with the objective of answering specific questions. Thus, AI tools cannot be used alone without verification by a human. To assess the applicability of an AI tool according to the clinical situation and type of imaging study, radiologists must understand the technical basis of the tool and have information on the data used to train the algorithm (number and type of data, robustness of the decision). Education about good clinical practice in the field of AI must be evidence-based.

Education for AI-assisted image interpretation and good clinical practice

The four major steps described in the official radiologist job description are derived from the goal of using an imaging study to provide therapeutic guidance. They consist of assessing the relevance of the imaging studies based on good practice guidelines; applying imaging study protocols; interpreting the images; and making management suggestions. Each of these steps can be optimized by using AI. Education should also involve technology surveillance activities including maintaining a record of all available AI tools and monitoring software updates.

Three main questions should guide the education provided to radiologists about AI: 1) Does the AI tool produce reproducible and reliable results? 2) Does the medical relevance of the results warrant the use of the AI tool based on pathophysiological data? 3) Does the AI tool provide meaningful improvements compared to current methods? Regarding this last question, as with all healthcare interventions, the ultimate goal of AI tool evaluations is to identify and quantify the clinical benefits to the patient and community.

Data protection and medical ethics

Radiologists who produce medical imaging data are also responsible for protecting the confidentiality of those data. Training programs should therefore include information on data protection (GDPR) and the obligation to inform patients that their data may be used and/or that AI tools may be applied to assist in making decisions that involve them directly (i.e., lesion detection and assessment of changes in lesions over time).

The 2018 French National Authority for Health (HAS) report underlines the importance of ensuring that the use of algorithmic systems complies with ethical principles; that the algorithms are predictable and accurate; that no losses occur relative to the clinical results; and that no drift occurs relative to the ultimate goal. The report also suggests the creation of a surveillance system focusing specifically on AI.

Education in informing patients about the imaging study and its results and in providing patient support

Informing patients that AI will be used to interpret their images will be a novelty that will have to be considered in the way we interact with patients. Concepts such as risk, verifying abnormalities, and likelihood of being ill may cause stress to patients. The radiologist must support the patients as they explain the results to them and must then direct the patients to appropriate care pathways. Radiologists will thus become the new internists; and with the assistance of synthesized electronic data, they will be providing precision, personalised, and participative radiology. This evolution will require greater emphasis on teaching radiologists about disclosing diagnoses to their patients.
Education in comprehending global healthcare data sets: big data

Global healthcare databases will combine imaging studies, quantitative laboratory test results, genetic test results, and clinical information. It may be worth considering implementing specific training in the use and analysis of these vast and heterogeneous data. More specifically, useful goals would be the creation of an observatory to confirm that practices are appropriate relative to requests and the establishment of a technology surveillance system geared towards public health and epidemiological objectives.

Promoting education and conventions

During initial resident training, depending on the stage of development in clinical practice, courses will be delivered as early as the foundation phase. The content will follow technological advances, as would be the case for a new branch of our profession. Residents will be informed of the existing France of university degrees (DU), inter-university degrees (DIU), master classes, and master’s 1 and 2 degrees, as well as conventions offering training on AI topics. Continuing medical education programs will have to be set up to provide practicing radiologists with appropriate training. The link between teaching and the industry could be enhanced in the field of AI.

Ethical and societal issues related to the use of AI in medical imaging

The advent of technological improvements (increased computation capabilities of machines, rapid development of robotics and algorithms, greater digital data storage and analysis capabilities) at a time when vast data sets are becoming available has led to the first applications of AI systems in the field of healthcare and, more specifically, in medical imaging. AI systems are powerful tools that can safely and rapidly perform automatable, repetitive, and tedious tasks at a distance and without interrupting the radiologist. They can also perform in-depth analyses of imaging data sets so vast that they are beyond the scope of human intelligence. The time and energy thus freed up by AI can be used by radiologists to focus on two crucial aspects of their work, namely, conducting an expert review of the medical data specific of each patient [24] and communicating the obtained information to the patient. AI and big data raise multiple ethical and societal issues that are listed in Fig. 4. These issues have been under debate by the French committee on bioethics (États Généraux de Bioéthique en France) since 2017. However, some aspects of these issues are discussed in this section.

AI, automated medical decisions, and liability

The acquisition, interpretation, decision, and databased-learning capabilities of AI systems (software) developed for healthcare share many features with robots (materials) [26]. As a result of these similarities, the lines of ethical reasoning
developed in the fields of AI and robotics frequently intersect [27]. One of the main focuses of debate is modulation of the responsibility of the professionals who use algorithms in their everyday practice. Some institutions, such as the French Data Protection Authority (Commission nationale de l’informatique et des libertés, CNIL), emphasize the risk of weakening the sense of moral responsibility towards others among professionals who use digital interfaces, as well as the risk of lessening the role for humans in the decision-making process regarding a diagnosis, as responsibility is being shifted to autonomous and self-learning decision algorithms. Thus, a potential conflict is emerging between the ability of humans to act autonomously and the complex, at times obscure yet reputedly infallible, logic of machines [26, 28]. AI will allow radiologists to delegate simple and repetitive tasks to machines. Automation of these machines will improve both the quality and the yield of the results provided (i.e., when using imaging for screening purposes). The boundaries of human responsibility regarding algorithm-assisted decisions may be re-shaped by these new tools. Furthermore, automatic learning raises the issue of medical and legal responsibility regarding decisions taken based on results provided by intelligent and self-learning machines. The algorithm at work within a machine relies on informatics codes developed by the designer. Responsibility for the actions of the machine may be viewed as falling on the designer, the user, or both [29]. The issue of responsibility may be further modified if the machine becomes capable of changing its informatics code and decision-making capabilities via its learning algorithm. Neither machines nor algorithms are recognized as autonomous legal entities. Consequently, the physician is viewed as entirely responsible for the diagnostic procedures performed in patients, even when all or part of the decision-making process is automated. Routine involvement of a human being in the decision-making process remains indispensable in the field of healthcare, as shown by several court decisions (Article 10, CNIL law, [30]). The radiologist acts as the 'guardian of the machine', i.e., as an active operator and not a passive user, and is therefore the guarantor of the consequences of the diagnostic strategy applied to the patient, even when this strategy is partially assisted or entirely applied by AI systems.

Biases, errors, and grey zones related to algorithms

The work performed by self-learning algorithms can result in biases and applicative errors. One risk is overfitting, in which the machine learns from a set of labelled data that does not apply to all population types (e.g., application of a tuberculosis-screening algorithm learned from chest radiographs obtained in population A to population B, which has different epidemiological and pathophysiological characteristics). The results produced by AI systems should therefore be considered with some measure of circumspection to avoid any decision-making mistakes that might result from bias or error [28]. The legitimacy of AI systems and the trust professionals place in them will be enhanced by this approach [26]. Supervision, feedback about previous experience, anticipation of failures, tracking, and the ability to modify algorithms [31] will help to control the process and retrospectively identify factors associated with good or bad diagnostic decisions, thereby contributing to a trusting relationship between humans and their machines.

Justifying the results provided by AI

The black box of a neural network is an algorithmic system whose input and output are readily observed but whose internal operations are difficult or impossible to understand, due to their extraordinary mathematical complexity. Thus, the intelligibility and demonstrability of AI systems raises enormous scientific challenges [31]. In other words, the logic underlying a learning algorithm may remain obscure to humans, including to the algorithm designers, in part due to the self-learning capabilities of the machines. Humans therefore experience difficulties following the logical reasoning of a decision-making algorithm. Transparency and comprehensibility may help to combat these difficulties but will require efforts in disseminating and actively sharing knowledge about algorithms within the medical and scientific community. In the field of healthcare, a diagnostic result must be justified. Such justification, however, is an empiria if the algorithmic process used to achieve the diagnosis cannot be explained by the physician who uses it. For the accreditation of AI systems, the French Standardisation Association (Association Française de Normalisation, AFNOR) may require that these systems be founded on the principle of justification, based on possibilities instead of probabilities, in order to maintain some level of demonstrability of the results.

Societal issues and collective regulation of AI in medical imaging

The technological solutions provided by AI constitute a major societal issue. Meeting the nationwide needs in terms of high-quality radiological competencies in the current setting of complex medical demographics is a challenge of the utmost importance for the authorities that collectively regulate healthcare professionals and policies [32]. AI systems will be able to perform certain radiological tasks for the entire population of the country. Thus, similar to the solutions provided by teleradiology, those delivered by AI may compensate for the dearth of radiologists in some geographic areas, thus providing patients and their physicians with fair and equitable access to high-quality radiological competencies.

Finally, regarding the deployment of AI technologies in research and clinical applications (Fig. 5), there seems to be a determination to develop positive, collective, and multidisciplinary regulatory measures within regulatory authorities, advisory and operational ethics committees [26, 33] and, perhaps, a national platform for algorithm auditing [28]. Radiologists will have an important advocacy role to play in this process, with the goal of defending their patients’ best interests.
The ten principles of AI in radiology

In addition to the 23 Asilomar Conference principles recognized by the radiology profession (Appendix C), practical guidelines, rather than recommendations, should be followed by all those involved, including radiologists, researchers, industrials, and public authorities. These guidelines are briefly presented here as ten general and organizational principles:

- the recognition of the importance of French radiological expertise by French and international scientific societies that are developing AI tools must be supported by a genuine collaboration and research contract;
- radiologists, who are active in the field, have an indispensable role to play in changing the architecture of databases (urbanization), evaluating and conducting the clinical validation of software, and actively monitoring the data produced over time;
- radiologists must be involved from the outset in the organization of imaging study data in healthcare facilities and in territories and regions. As they must act as guarantors of the data and of good clinical practice, radiologists must be integrated within an organized medical team;
- the organization of radiological care should be centered on the patient (for whom radiology is often at the center of the care pathway). The impact of radiology in the short and medium terms (classification, assistance with decision-making, etc.) will have to be visible and the confidentiality of patient data protected in the framework of 4P radiology (predictive, preventive, personalized, participative);
- AI tools should be used as a complement to the imaging study process to improve quality and safety in radiology (precision radiology to optimize sensitivity, specificity, and reproducibility and to minimize errors) and/or to complement and optimize radiology care by suggesting new indications (predictive and preventive radiology);
- an innovation dynamic must be set in motion among industrials, radiologists, and public authorities, with careful attention to data protection, ethical and scientific principles (articles L341-1 and following of the International Criminal Court code), and ownership of radiology data;
- the establishment of a fund dedicated to work in the field of AI (or digital) and radiology over the next 10 years would promote the development of industrial tools and of research and innovation;
- Nationwide organization of the data in a warehouse or data hub would ensure that patient management is coherent; images and associated data are of good quality; and imaging studies are relevant. Other advantages would include validation of new applications, promotion of research projects, and the production of national indicators (quality, relevance, public health, etc.);
- a regional organization would establish links between community and national healthcare centers and would allow the conduct of pilot experiments in one or more of the 13 regions of France;
- the evaluation of organizations for using AI software rests on the medical team concept. This evaluation should be conducted by peers, as recommended by the American College of Radiology (ACR) and supported by the French National Health Authority via the accreditation of medical teams.

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Appendix A. Glossary of the terms used in artificial intelligence applied to radiology

A.1. Glossary

Artificial intelligence: set of theories and techniques used to produce machines capable of imitating human intelligence

CADe (computer-aided detection): automated detection tool (e.g., automated segmentation of a lung nodule)

CADx (computer-aided diagnosis): automated diagnostic tool (e.g., determination that a previously detected lung nodule is malignant)

Classification: prediction of a category (e.g., the ACR score of a mammogram), as opposed to a regression task

Deep learning: subfield of machine-learning that uses multi-layered artificial neural networks
Detection: machine-learning task consisting in predicting where an abnormality is located in space
Labeling: Specifying the meaning of the information contained in the image, by explaining it; may be accurate (e.g., volumic segmentation of a tumor to determine its size and characteristics [contours, texture …]) or inaccurate (weak labeling, e.g., radiology report)
Machine-learning: subfield of artificial intelligence that allows the machine to learn how to perform tasks by using data, without having been specifically programmed to perform those tasks
Model: should be distinguished from an algorithm; refers to the function that has been computed (with the weight of each parameter)
Parameter: variable computed by the algorithm during the learning phase
Hyperparameter: variable defined before learning within the algorithm; this task is now performed by the data scientist.
Deep neural network: see deep learning
Segmentation: defining the contours of part of an image (e.g., organ, segment of an organ, or tumor)
Dataset: collection of data used to perform predictions
Learning phase: phase during which the model parameters are computed, based on dedicated data
Test phase: phase in which the general applicability of the model is evaluated, using data different from those used in the learning phase (although often from the same dataset)

A.2. Keypoints
The term ’artificial intelligence’ now chiefly designates supervised machine-learning.
Machine-learning tasks involve two phases, a learning phase that uses data dedicated to learning followed by a test phase that uses different data (often from the same data set) or by a validation phase (ideally using data from a different dataset).
The term ’deep learning’ refers to convolutional neural networks. The word ’deep’ refers to the network architecture consisting of multiple layers of artificial neurons.

Appendix B. Guidelines for using medical imaging data
L Boussel, JF Chateil, O Clément, L Fournier, A Luciani, C Oppenheim, P Puech, L Verzaux

B.1. Guideline 1: Commitments of the radiologist regarding collection quality for created and supplied data
• The radiologist must ensure that the database (for filing or storage) from which the images will be retrieved was established in compliance with ethical and scientific rules (articles L341-1 and following of the International Criminal Court code).
• The radiologist must ensure that the patient is informed about the use of algorithmic techniques for analyzing supplied images, in compliance with current regulations.
• The radiologist must ensure that the imaging modality, equipment, and acquisition parameters; signal collection conditions; and data computation methods have been validated by a radiologist and comply with state-of-the-art practice or with a prospective acquisition protocol validated by a radiologist and capable of providing an answer to the question asked.
• Regarding data acquired as part of standard patient care, the radiologist who supplies the images must ensure that these were acquired according to current protocols and in compliance with state-of-the-art practice, as recommended by scientific societies including the French Radiology Society (Société Française de Radiologie) and were supplied with a result disclosed to the patient in the form of a report.

B.2. Guideline 2: Compliance with data transfer rules
• The radiologist—or a radiologist representing the radiology team—who supplied the images agrees in transforming ownership of the data within the framework of the ongoing research project.
• All service providers who use or exploit the data must ensure that de-identification of the radiological images entered into the database is optimal, i.e., prevents patient re-identification and complies with current regulations. Special attention should be directed to the risk of re-identification from reconstructed images, e.g., via surface or volume rendering.

B.3. Guideline 3: Compliance with rules for managing and exploiting transferred data
• The person or persons who exploit the images must ensure compliance with current regulations as defined in the GDPR, which include the right to information, follow-up, traceability, and erasure of images entered into databases.
• The person or persons who exploit the images must comply with the recommendations issued by the French Board of Physicians (Conseil National de l’Ordre des Médecins) and French Data Protection Authority (Commission Nationale de l’Informatique et des Libertés)
• The person or persons who exploit the images must guarantee that, if valorization of the fruits of algorithm development is a possibility, then a contract must be established and signed, at the least, by the radiology team or teams that provided the data.
• The person or persons who exploit the images must undertake not to communicate the images or results of image processing to a third party without completing the required additional regulatory procedures. The list of these procedures should be obtained from the French Radiology Society (Société Française de Radiologie).
Appendix C. French Radiology adheres to the 23 Asilomar AI principles

To date, there is no universally accepted document for guiding activities in the field of AI, notably by developing good practice standards. As a preliminary to creating such a document, several specialists in AI and robotics met in January 2017 at the Asilomar Conference on Beneficial AI organised by the Future of Life Institute (FLI) and held in Asilomar, California. The Future of Life Institute (FLI) is a non-profit organization based in the Boston area and focused on mitigating the existential risks that threaten humanity, notably those generated by AI. At the end of the meeting, the participants adopted 23 principles, whose objective is to guide the development of AI. According to the available information, these principles have been endorsed by 846 researchers specializing in AI and by 1270 specialists in other fields. The French National Radiology Council (G4, Conseil National Professionnel de la Radiologie) has accepted the 23 principles, which are listed below.

C.1. Principle No. 1. Research goals in AI and radiology

The goal of AI research should be to create, not undirected AI, but AI that benefits the patients and physicians.

C.2. Principle No. 2. Research funding

Investments in AI should be accompanied by funding for research on ensuring its beneficial use including thorny questions in computer science, economics, law, ethics, and social studies, such as:

- How can we make future AI systems highly robust, so that they do what we want without malfunctioning or getting hacked?
- How can we grow our prosperity through automation while maintaining people’s resources and purpose?
- How can we update our legal systems to be fairer and more efficient in managing the risks associated with AI?


There should be constructive and healthy exchange between AI researchers and policy-makers.

C.4. Principle No. 4. Research culture

A culture of cooperation, trust, and transparency should be fostered among researchers and developers of AI.

C.5. Principle No. 5. Race avoidance

Teams developing AI systems should actively cooperate to avoid corner-cutting on safety standards.


AI systems should be safe and secure throughout their operational lifetime, and verifiably so where applicable and feasible.

C.7. Principle No. 7. Failure transparency

If an AI system causes harm, it should be possible to ascertain why.


Any involvement by an autonomous system in judicial/medical decision-making should provide a satisfactory explanation auditable by a competent human authority.


Designers and builders of advanced AI systems are stakeholders in the moral implications of their use, misuse, and actions.

C.10. Principle No. 10. Value alignment

Highly autonomous AI systems should be designed so that their goals and behaviours can be assured to align with human values.

C.11. Principle No. 11. Human values

AI systems should be designed and operated so as to be compatible with ideals of human dignity, rights, freedoms, and cultural diversity.


People should have the right to access, manage and control the data they generate, given AI systems’ power to analyses and utilize that data.

C.13. Principle No. 13. Liberty and privacy

The application of AI to personal data must not unreasonably curtail people’s real or perceived liberty.


AI technologies should benefit and empower as many people as possible.

C.15. Principle No. 15. Shared prosperity

The economic prosperity created by AI should be shared broadly, to benefit all of humanity.


Humans (radiologists) should be able to choose how and whether to delegate decisions to AI systems, to accomplish human-chosen objectives.

C.17. Principle No. 17. Non-subversion

The power conferred by control of highly advanced AI systems should respect and improve, rather than subvert, the social and civic processes on which the health of society depends.
C.18. Principle No. 18. AI arms race

Not applicable to radiology… in theory.


There being no consensus, we should avoid strong assumptions regarding upper limits on future AI capabilities.

C.20. Principle No. 20. Importance

Advanced AI could represent a profound change in the history of life on Earth, and should be planned for and managed with commensurate care and resources.


Risks posed by AI systems, especially catastrophic or existential risks, must be subject to planning and mitigation efforts commensurate with their expected impact.

C.22. Principle No. 22. Recursive self-improvement

AI systems designed to recursively self-improve or self-replicate in a manner that could lead to rapidly increasing quality or quantity must be subject to strict safety and control measures.

C.23. Principle No. 23. Common good

Superintelligence should only be developed in the service of widely shared ethical ideals, and for the benefit of all humanity rather than one state or organization.

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