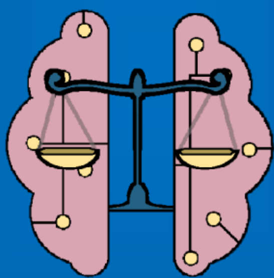
# The AI Fairness Definition Guide



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# Abstract

*The adoption of Artificial Intelligence (AI) in all sorts of automated systems and digital services creates concerns over biases with real world ramifications and harm. This guide aspires to help system creators (e.g., engineers working on the design, implementation, and deployment of AI models and user interfaces) understand how to define fairness in the social context of their systems by working together with stakeholders and experts from other disciplines. It does so by presenting a workflow that transcribes abstract fairness concerns of affected stakeholders to corresponding formalisms and practices that combine computer, social, and legal science viewpoints.*

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# Introduction

Artificial Intelligence (AI) affects people's lives by automating predictions, scoring, and recommendations. However, there are increasing concerns of whether AI systems are fair, especially since they tend to replicate or exacerbate real-world biases. The meaning of fairness depends on who is asked, and on the regulations and stakeholders that systems encounter in different markets. It also varies across predictive tasks (e.g., financial services, face verification, news recommendation, scientific search). The first step in recognizing biased AI consists of concretely defining fairness. Doing so assists the creation of policies and regulations, prevents the deployment of harmful systems, and supports algorithmic solutions for bias mitigation.

Since fairness is a malleable concept, it is hard to create one operational definition that caters to all AI systems, actors, and contexts. The lack of a one-size-fits-all solution is reflected in the many formalisms (e.g., mathematical measures) and practices presented in this document, which capture different opinions and contexts, and tend to contradict each other (Kleinberg, 2016). For example, proportional representation of minorities in positive classification outcomes could be at odds with equal accuracy between the minorities and the entire population.

As a system creator, you are called to select definitions of fairness from the algorithmic fairness literature or devise new ones. Your systems require technical definitions (e.g., mathematical constraints, or software engineering practices) to develop and evaluate, but social and legal sciences often express fairness via abstract terms, such as protecting underprivileged groups or participating in societal improvement. These terms organize the heterogeneous opinions of individuals into schools of thought or policies that are inherently different from technical language (e.g., they may be hard to quantify). This guide will help you orchestrate an interdisciplinary collaboration that converts non-technical concepts to technical definitions.

The authors worked on bridging the gap between abstract fairness statements and concrete definitions within the MAMMOth project; this is a European Union (EU) project that tackles bias under the intersection of multiple sensitive attributes (e.g., gender, race) and data source modalities (e.g., tables, images, graphs). It also follows a multidisciplinary approach, and one of its goals is to operationalize definitions of bias while accepting input from affected stakeholders. The project created a unique opportunity for exploring fairness under the computer, social, and legal sciences, and for investigating how to merge these domains in one workflow that accounts for context-dependent concerns of stakeholders. We followed this workflow in MAMMOth to extract its software and research requirements.

This guide publicizes the above-mentioned workflow, so that AI system creators can use it to derive fairness definitions tailored to their operational environment. We structure the proposed process as a series of five questions, which you can answer on a per-case basis to arrive at sensible definitions for your systems. These are:

**Who** should define fairness?
**Why** is fairness needed?
**Where & When** should fairness be applied?
**What** is considered a fair outcome?
**Which** practices should be followed?

The first two questions help extract the social context, and the last three identify how to incorporate context-specific concerns in factual systems. Final fairness definitions are not limited to philosophical terms or mathematical formalism, like constraints, but also include fair practices to be followed. Our approach reconciles complex sociological perspectives with software engineering by viewing AI systems as socio-technical ones, which means that they comprise intertwined technical and social aspects. For such systems, we summarize previously described challenges in three statements:

1. ***Fairness is context-specific.*** There is no general fairness definition that applies to every context or use case. In this guide, you will find – among other things – an overview of popular definitions from computer science literature. However, which ones are suitable depends on the specific situation you are studying; less common definitions could be preferable in certain cases.

2. ***There might be conflicting interests and opinions on what is fair.*** Different stakeholders might have different ideas on what constitutes a fair solution to a problem. For instance, think of an AI system that evaluates loan requests. Bank clients might want their personal circumstances and intentions to be part of the evaluation. Whereas lenders might think it is fair to provide impartial and systematic responses (although these may also contain biases that were not accounted for during AI system creation, like historical racism in training data). To make matters worse, there may be power relations and conflicting interests between stakeholders.

3. ***Fairness is multi-layered.*** That is, it needs to account for various aspects, such as technical, social, legal, and ethical. This guide is meant for AI system creators, so there is a focus on the technical aspects. However, these make up only a part of the problem; throughout this guide we recommend working in close cooperation with other disciplines to properly address the issue of fairness.

While selecting or creating fairness definitions for your systems from a wide range of feasible options, the presented methodology will let you work with social scientists to acknowledge the views of affected stakeholders, and with legal experts to comply with regulations. To this end, you will first get a clear idea of involved parties and their roles (Who), and be introduced to social science fairness objectives (Why). You will also find out where fairness interventions may occur within an AI system's pipeline and lifecycle (Where & When), and become familiar with common types of fairness definitions that may be reused or created, be they formalism (What) or practices (Which).

Parts of the process we outline are followed by many works, including research papers that start from specific concerns and contexts, propose suitable definitions of fairness, and then satisfy them through algorithmic means. This guide structures how you should approach the creation of similar fairness-aware AI systems.

# Who

## should define fairness?

### Goal

Learn about parties that should be involved in defining fairness and their roles.


### Summary

To create real-life technological solutions, combine research principles with fairness concerns of affected stakeholders. This requires co-designing AI systems with the stakeholders. Consult with legal experts to ensure compliance with laws and regulations, and work with social scientists to ensure that interests of stakeholders are adequately represented and integrated.


The process we introduce for defining an AI system's fairness involves several actors: a) system creators, b) affected stakeholders, especially from underrepresented or systemically oppressed groups of people (e.g., racial minorities), c) social scientists, and d) legal experts. The approach itself constitutes a mixture of *principlism*, which is the practice of following predetermined principles, with *pragmatism*, which is the acknowledgement of the reality stakeholders face. Below we discuss these standalone approaches and their combination.

A precondition for applying our mixed approach is to determine **who** are the stakeholders affected by your systems, because fairness will eventually be based on a combination of their views with applicable scientific standards and regulations. This section explains how you can interact with stakeholders. Indicatively of how important integrating their opinions can be, a broad range of interested parties was also consulted via a survey for the creation of the *Hiroshima Process International Code of Conduct for Organizations Developing Advanced AI Systems* (G7, 2023b), with which this guide is compatible.

Affected stakeholders are groups of people, such as underrepresented groups, or organizations that represent them, such as non-profit ones. To identify the groups, you must collaborate with social scientists (e.g., anthropologists, economists, sociologists, psychologists) and let the latter gather input through appropriate methods and techniques, such as focus groups. Product owners, that is, the people or organizations on whose behalf you create AI, are also stakeholders whose interests will be gathered. You might be a product owner yourself, in which case provide feedback independently of your capacity as a system creator. Let the social scientists lead any multistakeholder discussions.

## Principlism

Principlism refers to applying universally accepted – and therefore context-independent – ethical principles on a scientific domain. This term was first coined for medical bioethics (Beauchamp and Childress, 2001) but a similar assumption tends to be implicitly followed by AI fairness research and algorithmic fairness code frameworks (e.g., AIF360); both implement predetermined ethical principles that have been mapped to mathematical definitions. Popular fairness principles of this kind tend to gain approval by affected stakeholders in many social contexts (Saxena et al., 2019), although it is unknown whether the same approval would manifest in new contexts.

Regulatory frameworks also present principles that guide or mandate how fairness is defined. For example, in the EU market, fairness is one of the key requirements presented by the *Ethics Guidelines for Trustworthy AI* (AI HLEG, 2019), and one of the AI principles of the *Organization for Economic Cooperation and Development* (OECD, 2023). Compatibility with provisions or official recommendations requires the involvement of legal experts, especially when technical approaches for quantifying bias become loose indicators under legal framing (Xiang and Raji, 2019).

Sticking to principlism during AI system creation is an attractive prospect in that it involves only a few actors; under this approach, and besides the help of legal experts on determining compliance with market regulations, system creators would be the ones to select applicable principles from the literature. For example, the exclusion of protected characteristics (e.g., gender, race, national origin) from decision-making in the field of employment is laid down in *Title VII of the Civil Rights Act*[1] of the US, as amended[2]; this rare alignment between legal and technical language makes it clear that you should follow the algorithmic practice of not using these characteristics in AI predictions in the corresponding market. Furthermore, well-studied scientific standards are often incorporated into reusable code frameworks, which can drastically speed up the creation of new systems with well-tested code.

On the other hand, principlism has certain limitations. To begin with, this approach is too focused on the technical aspects, with the risk of missing both the social context and the side effects that applications may have on the real world (John-Mathews et al., 2022). To understand this claim, recall that there might be conflicting ideas of what constitutes fairness among different people, in different contexts, and across different perspectives (e.g., technical, social, legal) (Gerards et al., 2023). However, principlism promotes a top-down approach to defining fairness that is driven by AI creators; as technical definitions constitute only one incomplete perspective (Ruggieri et al. 2023), defining fairness on your own could result in missing the bigger picture.

In a similar vein, principlism creates the illusion that well-studied definitions of fairness, which are easier to compute or optimize, should be applied in every setting. One such definition is the ⅘ rule, which is

[1] *See:* Civil Rights Act of 1964 (Public Law 88-352).

[2] *See:* Public Law 114-95, enacted December 10, 2015.

widely popular in research circles and code frameworks. This stipulates that the ratio of accepted protected subgroup members should at worst be 80% that of the majority. However, this may be insufficient to satisfy the US legal framework of disparate impact in which it is often used; the latter requires significance testing instead (Watkins et al., 2022). Trying to circumvent this issue with more abstract principles, as regulations often do, rarely yields unambiguous definitions of fairness to implement, and instead requires context-specific exploration, like the one promoted by pragmatism below.

Another important limitation of principlism is that seemingly technical decisions can have consequences on people's lives in ways that are not anticipated by the principles. For example, binary classifiers that are made to have the same positive rates between males and females – which is a common process for preventing gender disparate impact – automatically forgo any protection of those who do not recognize themselves in one of these genders. In this case, what appears like a technical choice (usage of a binary protected attribute) is actually a political one that discriminates against a group of people.

## Pragmatism

Practical concerns of stakeholders are acknowledged by a different approach, called *pragmatism*. In this, instead of assuming the existence of globally true ethical principles, ethics are built from the lived experiences, perceptions, opinions, and concerns of stakeholders (John-Mathews et al., 2022). Discussions with multiple parties can support this process and highlight potentially diverging opinions on fairness (Whittaker, 2019). Particular attention should be paid to the struggles that oppressed groups face in the social situation under analysis.

If you followed a pragmatic approach to gather fairness definitions for an AI system, you would need the assistance of disciplines beyond computer science. First, cooperation with legal experts and social scientists would start from identifying affected stakeholders, such as legally protected and systemically oppressed groups of people in the relevant socio-technical context. Multistakeholder discussions should then be conducted to analyze stakeholders' opinions, interests and concerns, and extract definitions of fairness.[3]

Discussions would be organized and guided by social scientists to focus on the issues of all stakeholders, and to not extend beyond the context at hand, as this may inadvertently port definitions to settings they were not meant to address. You and legal experts would also participate, to respectively ensure that extracted definitions of fairness fit in your algorithms, and that regulations are followed.

As an example of what pragmatic feedback may look like, consider a security-critical facial recognition system deployed in a geographic region. Technical expertise may dictate that it is harder to analyze the faces of racial minorities, due to underrepresentation in training data. Therefore, to safeguard a fair use of the system for racial minorities, representative individuals from those groups, together with social scientists studying the issues they are facing, should be involved in determining on which system property to focus. One kind of feedback could be not to mistake same-minority members for each other (Cavazos, 2020). Different concerns may arise for facial recognition in different settings.

The main barriers in pursuing pragmatism are available resource limits, such as the time, budget, and effort to identify stakeholders and engage them in meaningful discussions. Furthermore, not everyone has the

[3] For example questions that could drive discussions with stakeholders, look at the UnBias toolkit.

necessary expertise to evaluate the technical details of an AI application (e.g., members of underrepresented groups cannot be expected to directly write specifications or design fiction). Hence, a transcription of such details to layperson terms is also needed.

A second shortcoming is that pragmatism is primarily a social science approach, and thus aims to summarize context-dependent concerns of stakeholders via interaction with social scientists. When system creators and legal experts are added in this collaboration, they bring different objectives (e.g., arriving at actionable definitions), and technical or legal language that is harder to align with the ways stakeholders understand and communicate social issues.

## Combining principlism and pragmatism

Principlism, like quantifying fairness with the previously described ⅘ rule, and pragmatism that acknowledges input from stakeholders are *not* mutually exclusive. In fact, we encourage a combination of both practices, as the first reduces complexity and brings rigorousness, such as adherence to legal guidelines or reuse of reliable systems, and the second acknowledges that systems are being applied on and affect the real world. We hereby describe an approach that aims to address the limitations of principlism with the incorporation of pragmatic practices. This way, we let stakeholder feedback drive the selection, adjustment, or creation of concrete definitions of fairness (Weinberg, 2022).

Our approach starts by letting system creators search for many applicable fairness definitions, based on principlism. Early prototyping or dataset auditing may be needed to make this search tractable. This exploration should not be considered as a form of system evaluation, but rather as a way of demonstrating simple concepts or statements about fairness, such as stating that a gender appears on average only one time in the top ten predictions for a recommendation system. Share these concepts in easy-to-understand formats (e.g., presentations) with social scientists and affected stakeholders to let them get a sense of algorithmic issues at play.

Then, social scientists can follow a pragmatic approach that lets the stakeholders determine what constitutes fairness using the provided concepts as a basis. Use the newly extracted definitions to update or create new principles and repeat the process until stakeholders are satisfied that their concerns have been addressed. All the while, enlist the help of legal experts to make sure that you comply with regulations. Make several repetitions of this workflow, including several rounds of stakeholder discussions. These are simpler than a fully pragmatic approach, as each discussion’s goal is not to produce a final definition but to refine existing concerns and compare them with the improved understanding of AI creators.

In the above collaboration, we set social scientists as a buffer between the roles of system creators and stakeholders – including product owners – that are involved in the definition of fairness. We do so because the process is challenging by itself. To give you an idea, consider an AI system that regulates university admissions (this example is retrieved from Costanza-Chock, 2020). We could work on fairness by correcting biases related to several intersecting protected attributes, such as race, gender, disability, or national origin. But working on fairness could also entail deciding whether attribute intersections in the admitted candidates should reproduce the proportions in the general population, or whether the system needs to correct the underadmission of certain groups in previous years. There is no universally right answer, but these aspects should be part of multistakeholder discussions.

The workflow we propose requires collaboration between the actors we already recognized (system creators, social scientists, legal experts, stakeholders) and emphasizes how systems end up affecting stakeholders in practice. Figure 1 summarizes the information flow between the actors; existing technical research is not an actor, but still guides the first system analysis that will be enriched or modified by the pragmatic stakeholder feedback retrieved by social scientists.

The time and effort costs that would have been incurred by adding more actors to the pragmatism approach partially persist, though reduced by clear-cut roles and interactions. Other types of influence between actors, like power dynamics between stakeholders or the influence of laws on everyday life, should be documented during the process of gathering pragmatic feedback.

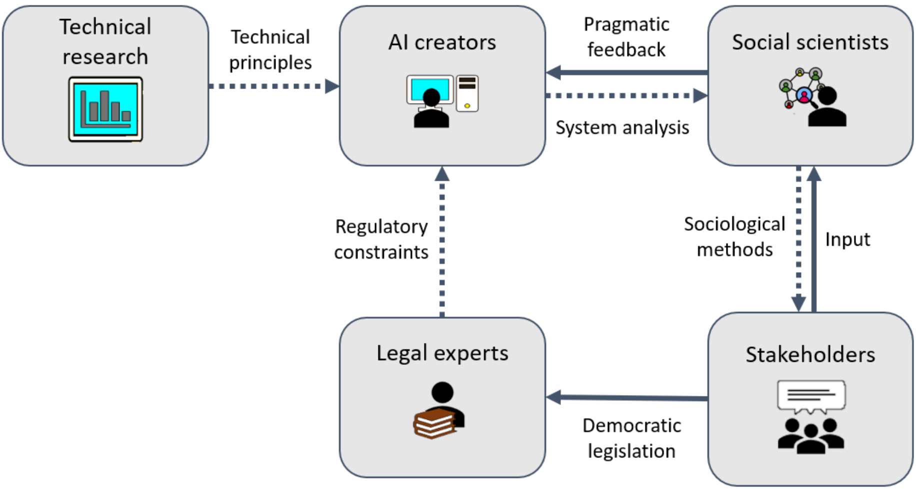


***Figure 1.*** *Information transfer between different actors under our approach for defining AI system fairness; dashed lines transfer principles.*

# Why

## is fairness needed?

### Goal

Learn about the interaction between AI systems and society, and the desired outcome of fairness interventions.

### Summary

If left alone, AI systems may learn from a biased reality and inject back biases that make it even more unfair. Determine whether you are implementing fairness to passively debias predictions (weak fairness) or to actively participate in societal improvement (strong fairness).

To understand the importance of **why** any kind of AI system fairness is needed, look at your systems as cogs of society that are prone to creating a feedback loop (Barocas et al., 2017). Without fairness interventions in place, they may not only directly harm individuals, but also exacerbate biases found in the real world, influence reality towards greater unfairness, measure the latter by gathering new or updated data, and then relearn to be even more biased.

This loop is demonstrated in Figure 2 and may create a vicious cycle of unfairness if left unattended. However, it also provides an opportunity to improve the world through algorithmic corrections and redesign; instead of exacerbating biases, systems can mitigate or reverse them (e.g., by temporarily creating the opposite biases) and eventually create a more balanced society as their outputs influence reality.

Most work on algorithmic fairness aims to achieve what is known as *weak fairness* (Kong, 2022), which debiases AI outcomes without looking at their broader societal impact. Concerns voiced during multistakeholder discussions, especially by vulnerable groups, might require you to work towards what is known as *strong fairness*, which actively challenges oppression and promotes fairness in society. This section explains the two concepts.

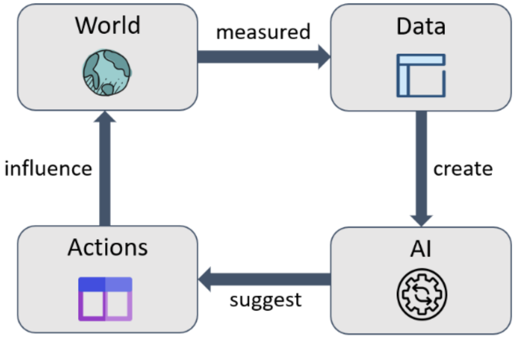


***Figure 2.*** *Feedback between AI and the world – adapted from Barocas et al., 2017.*

# Weak fairness

Weak fairness refers to removing bias from system predictions. Algorithmic bias mitigation research tends to implicitly assume weak fairness by making systems reach an approximate equilibrium under some measure of predictive performance when comparing groups of people – usually groups protected by legislation with non-protected ones. For example, false positive rates (e.g., the rate of wrong predictions for criminal recidivism) may be equalized between different races. Equilibria-based fairness easily leads to mathematical constraints but does not actively challenge oppression. For instance, equal false positive rates between races could give a false semblance of debiasing when ground truth labels used to compute the rates are influenced by historical biases like racism.

As an alternative to creating parity between mathematical measures, weak fairness may also look at *individualized symmetrical treatment*, which refers to treating all individuals the same, regardless of the effects of past or present-day discriminations. For instance, this could be expressed as a lack of group bias in the distribution (and not only in an aggregate statistic) of true or false positives, and true or false negatives. What “same treatment” entails depends on how reality is interpreted, and defining it means that input from stakeholders should be incorporated into AI data, for instance through few-shot learning to quantify acceptable predictive differences based on examples.

Although weak fairness does not take drastic action in improving society, it is not without merit. To begin with, it already breaks the feedback loop of reinforcing bias. For example, preventing a system from replicating racism or sexism found in its historical training data prevents the perpetuation of stereotypes, despite not accounting for the same types of discrimination elsewhere in society. Moreover, it may be challenging to identify a-priori how AI fairness interventions influence predictions or the world, in which case weak fairness becomes the only commonly agreed upon option.

# Strong fairness

Strong fairness aims to bring more access, opportunities, and life chances to all people (Kong, 2022). This viewpoint acknowledges that the legacy of long-term discrimination and oppression might require active redistributive actions to challenge discrimination by influencing the real world. This oppression can be understood as historical biases that have infiltrated learning data (e.g., biased jurisdictional decisions), but can also be found in societal structures that correlate with sensitive characteristics (e.g., zip codes correlating with race).

Consider, again, the example of university admissions provided in the previous section. Forms of strong fairness could include correcting the underadmission of certain groups in previous years, or could place equal importance on both more and less affordable extracurricular activities that influence the access to universities, given that some groups struggle to pay for expensive ones (Giovanola and Tiribelli, 2022).

Strong fairness also safeguards every person's *right to justification* (Giovanola and Tiribelli, 2022), that is, the right to receive explanations and understand the reasons behind AI outcomes, and the possibility to appeal decisions they consider unfair. The same prospects have been identified by independent schools of thought too; explainability is a key scientific standard described in the Which section, and the option to appeal decisions is part of *TrustAIOps* that ensure ongoing quality in the Where & When section.

Thinking in terms of strong fairness also means questioning the very purpose of the AI system, what it achieves, and its effects on society. There should be documentation of whose opinions and beliefs are being implemented, who is benefiting from the implementation, and who might be negatively affected. As mentioned before, this requires analysis of the social context and discussions with stakeholders.

Overall, strong fairness reframes the purpose of AI systems to improve society. For example, it may make hiring laxer for under-represented genders in certain fields to improve the perception among their members and encourage participation by all genders. Similar practices are known as *inverse discrimination* or *reverse discrimination*, given that the goal is to actively try to adjust society to protect future individuals at the potential cost of -at first- disproportionately aiding previously discriminated groups. Since this can create backlash, you should seek legal advice for the correct interpretation of anti-discrimination mechanisms. Moreover, this approach can cause side effects and unintended consequences, and therefore requires a socio-economic and political impact assessment too.

# Where & When

## should fairness be applied?

**Goal**

Get a sense of where fairness definitions can intervene within an AI system lifecycle.

**Summary**

Making AI systems fair is not a one-time intervention, but a consideration at each step during their lifecycle; fairness spans fair design, development interventions, and ongoing practices to maintain quality.

AI systems are software projects. Thus, their lifecycle spans the three main stages of software development presented in Figure 3: a) design, including planning and requirement gathering, b) development of the main system, and c) maintenance over time. Apart from bug fixing, insights gathered during maintenance may lead to redesign and additional development down the road. During all stages, identify **where and when** to apply fairness-aware interventions (Calegari et al., 2023; Rana et al., 2023). Interventions include ongoing processes that extract an updated understanding of AI risks and lead to redesign too.

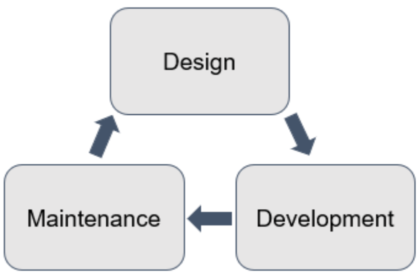


***Figure 3.*** *Software lifecycle.*

Regardless of whether systems require maintenance, fairness analysis and bias treatment methods could be needed at any step of each one's creation pipeline. Fairness analysis should start early on, by involving stakeholders in design fiction (e.g., mockups, user stories), and by determining whether business objectives are inherently unjust. For example, widespread population surveillance may be unjust even if it does not discriminate between population subgroups.

During development, identify biases relevant to the selected fairness definitions. Do this for each AI component, before biases are picked up and exacerbated by subsequent components. Do this without losing scientific rigor. For example, do not blindly violate preconditions that algorithms require to properly run, but replace components with equivalent ones that are compatible with fairness interventions.

Some systems, such as chatbots for events, have a short life and are later discarded alongside their results. These do not require extensive maintenance, and definitions of fairness like the ones of the What and Which sections are sought mostly during design and development. Conversely, systems deployed for a longer time also require fairness oversight during maintenance. To give you an idea of such systems, they could be multimedia generation or classification services that are accessible through the Internet (e.g., ChatGPT's chatbot, facial identification services), or recommendation components of online platforms (e.g., that select which advertisements to show to each user in search engines or social media).

Maintaining an oversight means that you should not treat technical and non-technical methods for introducing fairness as one-of procedures, but as continuous processes to be followed throughout each system's lifecycle. We next present in greater detail how fairness concerns can be incorporated into each stage of said lifecycle.

# Fair design

There exist various software design methodologies. The *Agile* approach (Beck et al., 2021) quickly iterates through new versions of systems and adjusts them through input from stakeholder. Others disentangle design and implementation, thus reducing costly interactions between developers and system owners or users. Regardless of the exact methodology, some initial phases include user input and the extraction of requirements, usually followed by steps like the construction of design fiction, system architecture, and application interfaces.

When fairness is added as a requirement of AI systems, their design must be appropriately modified. For instance, stakeholders involved in the design, such as owners and users, will also include all the affected parties identified by social scientists and legal experts. Similarly, new system requirements should be extracted, and existing ones adjusted. In practice, it can be difficult to involve underrepresented groups in more technical aspects of the design, but you should at least acknowledge their pragmatic expectations. Some definitions of AI fairness are also imposed "by design", and therefore lead to further modifications at this stage. Overall, fair system design may require several iterations before implementing even the first prototypes. Many of the smaller iterations can be prevented if fairness is recognized early as a system goal.

For longer-life systems, or those designed with Agile methodologies, iterating through new versions requires tracking how bias or fairness considerations evolve. Evolution could arise either from changes in the system itself, changes in the deployment environment (including updates of regulations), or a more advanced understanding of how systems interact with society. Tracking evolution with regards to fairness has crystallized in the field known as *TrustAIOps* (Li et al., 2023).

This follows an Agile methodology that includes iterative refinement of system fairness by gathering feedback during operations in the deployment context.

## Development interventions

Bias can be unpredictable and arise at different steps of AI system creation, given that different components emphasize different underlying aspects of data. Even worse, subsequent steps may pick up leftover or new unintended biases in the outcomes of previous processing and exacerbate them to an irreversible degree. Understanding where bias comes from should start by scrutinizing your data mining and processing workflow. For example, bias could arise from interactions with system creators and their unconscious biases during training and validation, potentially unfair societies from which data are gathered, or biased data gathering practices.

A typical workflow is presented in Figure 4 alongside example datatypes. In this figure, AI creators work with existing data, preprocess those, and use them to create models, such as neural networks. The outcomes of the latter are post-processed, for example to be converted to formats easily parsable by humans, and finally validated in terms of meeting desired objectives, such as accuracy or fairness. Depending on the outcomes of validation, the steps of this creation process are revisited and modified to address found issues, such as predictive biases.

Asserting fairness cannot be summarized only in terms of one measure extracted at a single step of the above workflow on one dataset; the full process needs to be safeguarded, so that systems can also generalize any lack of bias that is observed in a few (training, validation, and testing) datasets under lab conditions to factual applications. In other words, AI systems should not only be fair in one circumstance but be *robustly fair*. Conversely, not treating bias at early steps may irrevocably embed it in the dataflow in ways that are hard to catch and quantify later. This last issue will likely be a byproduct of any dimensionality reduction within AI components, for example due to entangling proxies of predictions with sensitive attributes.

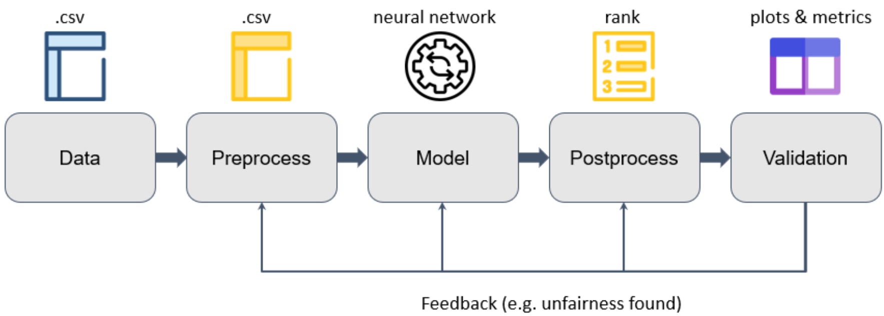


***Figure 4.*** *AI system creation pipeline.*

Ideally, fairness should be assessed just before, during, and after each step. Ask yourself how the outcome of previous steps can affect each subsequent one's inputs, and whether inputs could exhibit biases forewarned by domain expertise, stakeholders, and legal experts. Then, identify mechanisms that work inside steps that may be able to pick up that information and use it to influence outputs. For example, create informed hypotheses on whether AI components identify correlations between protected groups of people, or on whether information is being compressed (e.g., when creating embeddings) with mechanisms that could ignore the behavior of minorities.

Modern AI further tends to reuse pretrained components (especially large language models – LLMs) that serve as embedding mechanisms or publicly available initial states to be fine-tuned on new data. Unfortunately, many publicly available models are known to create biased outputs (e.g., Thakur, 2023 unveils LLM sexism).

If left unchecked, dataset and model biases of reused modules will also leak into your pipelines. For this reason, prefer either working with models that employ some corrective measures pertaining to the required type of fairness. Also perform bias detection, and any necessary mitigation, on pretrained model outcomes.

# Ongoing quality

After producing AI outputs, continue interacting with stakeholders to assert that their idea of fairness is correctly implemented. During cross-examination, keep a balance between justifying outputs as part of a fair process and accommodating constructive criticism. Do not over-rely on technical justification, as this would be another exhibition of principlism.

Throughout, try to make created systems explainable and follow processes that are understandable by the stakeholders; these are prerogatives of good scientific practices explored in the Which section. Furthermore, include the possibility for appeals against automated decisions, and be open to incorporating this feedback in maintenance, especially for longer-life systems. This can be part of the *TrustAIOps* employed for the fair design of new system versions.

Furthermore, implement processes that monitor the outputs of deployed systems and check if they work properly or reproduce biases. Most fairness formalism can be monitored with warning mechanisms akin to those of test-driven or metric-driven development. For example, check for distribution shifts in input data (which mirror changes in society) that either require greater corrective actions against already addressed biases or produce new forms of bias. Monitoring may involve continuous integration that asserts measure values both periodically and before deploying new system versions.

On the other hand, it can be hard to automatically check for adherence to non-mathematical fairness definitions. Aside from imposing certain processes by design, such as restricting access to specific system states or outputs, actively rechecking for non-technical definitions of fairness can be a lengthy process that slows down prototyping and development, especially if non-technical people need to be consulted. As a middle ground, consider periodic personnel training and evaluation of your methodology.

# What

## is considered a fair outcome?

Goal

Learn about popular philosophical and mathematical fairness formalism.

Summary

Fairness is expressed either in philosophical terms, or as mathematical measures and constraints. The two fields adopt different outlooks but often arrive at similar principles. Assess your systems under many existing definitions and use the outcomes as examples to jump-start multistakeholder discussions.

Our suggested workflow gathers pragmatic stakeholder feedback, which you will use to model **what** is considered a fair outcome. To this end, work closely with social scientists to accurately transcribe gathered feedback to concrete fairness definitions. Pre-existing or new definitions that apply on AI systems are either philosophical and mathematical formalism explored in this section[4], or broader scientific standards and regulations that you will find in the Which section.

We already mentioned that you should enlist a wide range of fairness definitions to assess your systems at first and provide the assessment's outcomes to multistakeholder discussions (e.g., via presentations). For example, previous fairness measures can serve as examples of how to create new definitions by interlaying simpler concepts (Roy, 2023). In this process, not every type of prospective bias will be captured by your analysis, and not all found imbalances will reflect actual concerns. Keeping this in mind, we reiterate that you should avoid principlism that would select from existing definitions without listening to stakeholders. Our recurring example of comparing false positive rates between

[4] Find more fairness formalisms in the Data Ethics Decision Aid (DEDA) handbook.

groups, which is a type of disparate mistreatment described in the mathematical definitions below, may be ill-suited for adoption when the ground truth data used in the evaluation are also biased.

Here, we present fairness formalisms of two kinds: philosophical statements, and mathematical expressions. The former transcribe abstract concerns into actionable terms and are predominantly used by social scientists, whereas mathematical expressions reflect the outcome of studying data or prediction imbalances from an algorithmic standpoint.[5] Recent attempts have been made to bridge the conceptual gap between the two fields and we show how some philosophical terms map to mathematical formulas and conversely.

## Philosophical definitions

A philosophical framework for expressing fairness that is popular in social sciences is distributive justice. This examines how benefits and burdens should be distributed between members of society. For example, it could stipulate how decision-making or recommender AI systems should allocate goods, like food donations, burdens, like interest rates, or services, like access to healthcare. While following such definitions you can pursue either weak or strong fairness.

As a starting point, we provide three popular types of distributive justice to follow or adjust (Khan et al., 2021): strict egalitarianism, the difference principle, and luck egalitarianism. There are also moral approaches to fairness that do not fall under distributive justice. Two of them are deontic justice and representational fairness.

[5] Bias in computer science is a broader term that also refers to deviations from expected values, and not only to fairness-related concerns.

**Strict egalitarianism** (Carens, 1981) stipulates that every person has access to the same level of goods, burdens, and services. This may be at odds with making different predictions for each individual and becomes the justification behind preventing AI from determining who gets access to basic human rights (Walzer, 2008), like the right to vote.

As an alternative to setting the predictions themselves as the subject of egalitarianism, some AI systems could be considered strictly egalitarian if they equalize some derived property across all people. For example, the numeric errors between predicted and true scores could be a type of burden that AI creators could try to equalize between each human data sample.

**Rawls's difference principle** (Rawls, 1971) justifies inequalities among members of society if they bring about benefits even for the least advantaged. When following this principle, take care to not disadvantage the least advantaged (Franke, 2021). In practice, adopt game theory maximin/minimax goals that aim to maximize the worst system utility across all groups of people (Ashrafian, 2023). System utility could correspond to the accuracy of AI predictions, or to the latter's differentiable relaxation into a machine learning loss function (Rahmattalabi et al., 2019; Kang et al., 2022).

**Luck egalitarianism** (Arneson, 1990; Cohen, 1997) is a variation of strict egalitarianism that considers every person's starting point in society as the result of both the social situation into which they were born, and their biological potential. It thus pursues redistribution of burdens, goods, and services only where inequalities can be attributed to someone's starting point, and leaves in place inequalities which are the consequence of personal choices. In practice this could be expressed by bounding distributive outcomes to an acceptable range (Anderson, 2007). The algorithmic definition of explainable fairness (Shulner-Tal,

2022) also prevents the mitigation of biases that are the outcome of conscious decisions.

**Deontic justice** (Parfit, 1997) is not concerned with an unequal situation per se, but rather with the way in which that state was produced, based on the combination of the historical and social context. Under this perspective, it is important to study the context itself and understand which groups of people have been discriminated against in the past and how forms of historical discrimination can affect AI systems in terms of fairness.

This type of justice does not lead to closed-form mathematical definitions of fairness but suggests that part of selecting them should involve consideration of the historic and contemporary factors responsible for broader systemic imbalances (Binns, 2018). Deontic analysis can also be used to derive mechanisms that model biases; we will later see that counterfactual fairness may take advantage of this modeling to remove bias by making the predictions that would occur in an ideal would-be fair world.

**Representational fairness** (Binns, 2018) aims to fairly represent different identities, cultures, ethnicities, languages, or other social groups. In practice, it could be defined to achieve the same rate (or some other metric) of representation as the real-world groups. When uniform random sampling is performed on populations to gather datasets, this process becomes identical to disparate impact presented later in that it aims to create equilibria between representation rates over gathered data. However, dataset generation is rarely devoid of bias, at worst due to statistical noise, and the true (in the entire population instead of dataset) rates of representation need to be considered; dataset-derived rates may only serve as proxies when there is no other alternative.

When strong fairness is required, replicating the representation of oppressed groups may not be enough; fair representation may include additional boosts for certain groups. Look at the example of boosting under-represented genders in hiring automation when strong fairness was first introduced.

## Mathematical definitions

Mathematical fairness measures and constraints can be set as objectives of AI systems. Several such definitions exist in the literature (Castelnovo, 2021), with the most popular types being presented here. Some of these are derived (Barocas and Selbst, 2016) from early legal efforts at codifying fairness, but have since then been established as technical principles. For example, disparate treatment and disparate impact definitions originate from the namesake legal terminology of US Supreme Court decisions[6].

Here, we present several definitions that are popular in the computer science literature. Each of them offers a certain flexibility in analyzing slightly different contexts, which has led to the creation of comprehensive roadmaps on which to apply in certain kinds of known contexts (Ruf and Detyniecki, 2021). However, contrary to their widespread use in research papers, they cover only a subset of known fairness concerns. As such, they can only serve as a basis from which context-specific definitions of fairness can be derived.

Explored definitions are designed for weak fairness by imposing parity between individuals or groups of people under system performance

[6] *See:* Case Griggs v. Duke Power Co., 401 U.S. 424, 91 S. Ct. 849, 28 L. Ed. 2d 158 (1971) first recognized "disparate impact": https://www.publicjustice.net/what-we-do/access-to-justice/disparate-impact.
*See for the conflicts between "disparate impact" and "disparate treatment":* Ricci v. DeStefano, 557 U.S. 557, 129 S. Ct. 2658, 174 L. Ed. 2d 490 (2009).

measures of choice. Still, their formulas are often flexible enough to support strong fairness by placing different weights in the balance between groups. For example, given weak fairness that equalizes the fraction of positive predictions between population subgroups, strong fairness could boost the fraction for oppressed groups.

The greatest advantage of mathematical definitions of fairness is that they fit in existing algorithms, such as in the regularization of neural network backpropagation, and in the predictive constraints of linear programming. A different usage pattern is to create proxy definitions that apply on some components of an AI system pipeline (e.g., interventions to apply during preprocessing) that end up creating improvements under different – and potentially a wide range of – definitions at system outcomes. These improvements may be mathematically corroborated but measured only empirically.

In line with the potential incompatibility of different social contexts, it is known that not all mathematical definitions of fairness can be simultaneously satisfied. Various impossibility theorems (Kleinberg, 2016; Miconi, 2017) codify this statement for predictors that are neither infallible nor constant. To get an idea, the impossibility theorem provided by Miconi (2017) shows that non-perfect non-constant predictors cannot simultaneously satisfy the mathematical definitions of disparate impact, equalized odds, and predictive parity. Intuitively, this happens due to reuse of the same base quantities in different assessment measures that are optimized at different points.

**Counterfactual fairness** (Kusner et al., 2017) estimates the attribute values that individuals would have had in an imaginary perfectly fair world and makes predictions based on those. Typical variations of counterfactual fairness consider mostly weak fairness that mitigates the effect of biases on AI predictions. But counterfactual mechanisms can account for strong fairness assumptions too, by including the end-effect of AI on society in their modeling. Usually, there is no process to verify the causal assumptions of bias generation modeling, but such mechanisms can be agreed upon during stakeholder discussions; we already mentioned that extracting them is a type of deontic analysis.

**Disparate impact** (Kamiran and Calders, 2012) mitigation refers to protected and non-protected groups being proportionally represented within positive predictions. This constraint is known as *demographic parity*, but rarely imposed as-is; mathematical relaxations create fractional comparisons or differences between the fractions, like the ⅘ rule, to quantify disparate impact mitigation and create objectives that can be optimized via machine learning. This objective tends to be at odds with improving AI accuracy, and on certain datasets its imposition can only make systems worse than producing a constant output (Pinzón, 2023). Recall that mathematical relaxations of disparate impact may be weaker than the namesake US legal term (Watkins et al., 2022).

Given that the causal modeling of counterfactual fairness involves latent variables that are statistically independent from the groups of people on which fairness is defined, there is an equivalence between counterfactual fairness over the entire population and disparate impact (Rosenblatt and Witter, 2023). Even in this rare case where different definitions of fairness are compatible, they serve different purposes; causal mechanisms satisfy deontic explainability of biases, and can be used to make sense of the bigger picture, whereas disparate impact is easier to understand as an objective.

**Disparate mistreatment** (Zafar et al., 2017) mitigation refers to similar rates of making mistakes between protected and non-protected groups. For binary classifiers, this often takes the form of equal false positive rates, false negative rates, precision, or recall. Of these forms, false negative rate equality is also known as *equalized odds,* and precision equality as *equal opportunity*. Other misclassification measures may also be applied.

All notions of disparate mistreatment rely on unbiased ground truth to compute errors, and we reiterate that this may be hard to procure. Mitigating this type of bias is similar to the difference principle; it aims to equalize the lack of benefits instead of the actual benefits to the less privileged, but these two concepts often share a primal-dual relationship (e.g., accuracy and the overall misclassification rate of a classifier sum to 1, which means that equalizing for one over a set of data samples equalizes for the other too).

**Disparate treatment** (Peffer, 2009) refers to biases that arise from using the sensitive attribute to make predictions and originates from corresponding US legislation. This maps to the individualized symmetric treatment expression of weak fairness and is only applicable to predictions that utilize attribute values (e.g., attribute columns in tabular data, different classifiers per age group in images) and does not account for attributes correlated with the sensitive ones.

**Individual fairness** (Fleisher, 2021) constraints stipulate that the distance between any two predictions should not exceed the distance between corresponding individuals and is also an example of individualized symmetric treatment. Defining how distance should be computed (e.g., it can be proportional to a p-norm) leads to different variations of individual fairness. Distance computations tend to create unintuitive interpretations for multidimensional data. This definition does not have a strong fairness counterpart.

**Multi-fairness**. Despite previously mentioned impossibility theorems, stakeholders tend to have multiple fairness concerns. Addressing these simultaneously is known as multi-fairness. This takes four main forms:

a) Satisfying multiple variations of the same type of fairness, as happens when disparate mistreatment is mitigated for both false positive rates and false negative rates.
b) Satisfying multiple types of fairness for the same protected attribute value corresponding to social groups or subgroups, as for example happens when aiming to protect women from disparate mistreatment while also adhering to individual fairness principles.
c) Analyzing sensitive attributes with multiple potential values, which correspond to multiple protected groups. These may compare each group with the rest of the population or compare all groups pairwise. For example, gender may not be a binary split between men and women but also include non-binary groups.
d) Considering the intersection of multiple sensitive attribute combinations (e.g., of gender and race) that correspond to several subgroups to be compared with each other.

To make matters more complicated, multi-fairness also covers combinations of the above, such as including different fairness measures for different attribute combinations. Two challenges of addressing multi-fairness are the aforementioned barrier between conflicting definitions, and that combinations of multiple sensitive attribute values often partition data into many groups of few (e.g., zero) members that prevent statistically confident analysis. As of writing, addressing these challenges is still the subject of research.

# Which

## practices should be followed?

**Goal**

Learn about mandatory practices that should accompany fairness definitions.

**Summary**

Fairness frequently requires adherence to scientific rigorousness and human-centric design. Also follow international and local regulations. In many cases, regulations are at their infancy and may be updated in the future – likely following the EU's trustworthy AI framework.

In addition to philosophical and mathematical principles, definitions of fairness can include broader scientific and legal standards. Of these, scientific standards maintain rigorousness and ease of system use, and regulations consist of rules and recommendations laid out by the legal overseers of markets and services. Both kinds of practices are tied to the markets that AI systems affect and operate in. Thus, they may lie outside your control as a system creator.

Here, we provide a brief overview of practices that you may need to be aware of before entering new markets, so that you can work more easily within their boundaries once you start creating AI systems. The details provided here are not applicable everywhere and may evolve over time. Much of the material is devoted to current EU regulation, as you will see that this has a worldwide effect. Work with legal experts to properly follow country-wide and international laws.

## Scientific standards

Fairness may coalesce measures and constraints with standards of scientific quality, namely of rigorousness and of human-centric design. These are frequently recognized by regulations too. We present the latter separately because scientific standards lie closer to technical specifications in that, once selected, they are easy to follow by integrating state-of-the-art research outcomes in AI system creation.

**Scientific rigorousness** ensures that applied fairness definitions are achieved not only in exploratory scenarios under lab conditions, but also when AI is deployed in markets and starts affecting real people. Two cornerstones of rigorousness that are neglected in many systems, especially LLMs (Narayanan and Kapoor, 2023), are the ability to generalize and robustness. We now explore these concepts.

First, principles and system prediction correctness should generalize beyond training examples, that is, to new data. Balance between overfitting and underfitting with train-test-validation data splits and hyperparameter tuning. For example, neural networks with too few parameters will overgeneralize, but too many parameters will reduce testing correctness, especially for underrepresented groups. Critically examine default domain hyperparameters (including machine learning rates and the number, type, and breadth of neural network layers) before using them in new systems.

Additionally, AI systems should exhibit satisfactory correctness and adhere to fairness definitions for out-of-distribution data. Robust systems are those not easily misguided by small input perturbations or conscious (e.g., malicious) attempts at modifying predictions with input changes that are nigh-imperceptible to humans. In addition to safety against input perturbations and adversarial attacks, robustness should also safeguard against "poisoning" of training data to misguide AI systems – this could co-exist with real world social biases.

**Human-centric design** should accompany scientific progress to help both operators and stakeholders of AI systems. Fairness is already one aspect of such a design, but making systems friendly to humans is tied to more considerations. To begin with, data privacy is an important concern to garner trust from people whose data are being processed, especially throughout the EU, where privacy has been codified through the GDPR.[7] Data security directions can also include generative adversarial privacy that safeguards against reconstruction of user data; through this data security mechanism, the parameters of a generative model are extracted from the data themselves (Huang, 2017).

Furthermore, created systems should be easy to deploy and replicate so that their fairness can also be studied by independent third parties. To simplify deployment, follow good algorithmic design principles like benchmarking, replicability, and documentation. While creating AI, remain aware of the overarching fairness concerns arising from regulations and input from stakeholder.

# Regulations

Integrating applicable AI legislation and ethical considerations in your systems is an essential process for market deployment. But the advantages of doing so also transcend to unregulated contexts, since fairness-oriented design and AI legislation are emerging worldwide (Jones et al., 2023). A market you should pay special attention to is the EU, where comprehensive and legal bidding regulation, especially the proposed AI Act[8], is expected to provoke global legislative efforts for AI systems. This is called the *Brussels effect* and is expected to resemble

[7] *See:* General Data Protection Regulation (2016/679).
[8] In April 2021, the European Commission proposed the first EU regulatory framework for AI.

the impact of GDPR, given that a substantial majority of providers put into service systems in the EU.[9] To help you acclimate to new markets that are influenced by this effect, you will later find an overview of legal tools for trustworthy AI in the EU.

Several countries introduced relevant legislation after the proposal of the EU AI Act in 2021 and can be considered part of the Brussels effect. Brazil proposed law *2338*[10] of May 2023 regarding AI. Canada proposed the *Artificial Intelligence and Data Act*[11] in June 2022. China issued the *Interim Measures for the Management of Generative AI Services* in July 2023 and the *Provisions on the Management of Algorithmic Recommendations in Internet Information Services* (China Law Translate, 2022). The US issued the *Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence* in October 2023.[12] AI fairness legislation was also adopted by some US states, like California, Connecticut, and Vermont (Engler, 2023; Cave and Paisner, 2023).

All the legal tools for AI systems worldwide are either in their initial stages, with their implementations yet unseen, or non-binding. Thus, let your collaborating legal experts continuously reassess deployed systems within regulatory fairness as the systems or laws change. This will often entail following a risk-based approach, where systems are re-examined

[9] Article 2, European Commission, Proposal for a Regulation of The European Parliament and of the Council laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts COM/2021/206 final.
[10] *See:* Bill nº 2.338/2023 available at: https://www25.senado.leg.br/web/atividade/materias/-/materia/157233.
[11] Part of the Digital Charter Implementation Act, 2022 (Bill C-27) available at: https://www.parl.ca/legisinfo/en/bill/44-1/c-27.
[12] Exec. Order No. 14110, 88 FR 75191, pp. 75191-75226 (October 30, 2023) available at: https://www.whitehouse.gov/briefing-room/statements-releases/2023/10/30/fact-sheet-president-biden-issues-executive-order-on-safe-secure-and-trustworthy-artificial-intelligence.

on various aspects of trustworthiness upon changes. You can do this within the scope of fair design's *TrustAIOps*. Keep in mind that not all existing legal instruments that enforce rules aim to have the same effect, and each oversees different markets.

Respecting the legal provisions of regulations may be mandatory, but implementing guidelines and recommendations is not. Nonetheless, satisfying a wide range of guidance for AI systems not only increases readiness for subsequent mandatory legal rules, but also contributes to business reputation and is considered an industry best practice. For example, NIST's *AI Risk Management Framework* (Tabassi, 2019) and its accompanying playbook rely on the US *National Artificial Intelligence Initiative Act*[13] but are intended to be voluntary, rights-preserving, non-sector-specific, and use-case agnostic for AI providers.

Another international non-binding legal attempt to support AI creators is the *Hiroshima AI process of the International Guiding Principles on Artificial Intelligence* (G7, 2023a) and the *Code of Conduct for Organizations Developing Advanced AI Systems* (G7, 2023b). This is based on the OECD *AI Principles*, and encourages entities worldwide to enforce detailed suggestions after identifying potential system risks.[14] Unlike the approach adopted by the EU AI Act, which classifies systems based on fairness-related risks, the Code of Conduct sets broader legal boundaries in relation to risks in certain critical sectors (e.g., nuclear risks, threats to democratic values, and human rights).

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[13] US National Artificial Intelligence Initiative Act of 2020 (P.L. 116-283) available at: https://www.ai.gov/wp-content/uploads/2023/04/National-Artificial-Intelligence-Initiative-Act-of-2020.pdf

[14] *See*: no1 of the Hiroshima Process "International Code of Conduct for Organizations Developing Advanced AI Systems".

## Trustworthy AI in the EU

In the EU environment, several measures apply when providers (notwithstanding their establishment) place on the market or put into service AI systems or their produced outputs.[15] The steps that you should follow as a system provider before deployment and operation can be broadly divided into two parts. First, the *Ethics Guidelines for Trustworthy AI* (AI HLEG, 2019) should guide all processes. Second, comply with the upcoming EU *AI Act* by identifying the level of risk of your systems. These two parts are explained in greater detail below.

Implement the internal protocols of the above two instruments to address existing or prospective issues regarding your systems' trustworthiness. Figure 5 presents effective tools that can help you. Of these, the *Assessment List for Trustworthy AI* (ALTAI) (European Commission, 2020) provides questions that – if correctly answered – let systems comply with the seven EU requirements for trustworthy systems. Then, *capAI* (Floridi et al., 2022) performs internal control for the *AI Act*. For the US, the playbook for the *AI Risk Management Framework* serves a similar purpose.

[15] *See:* Article 2, European Commission, Proposal for a Regulation of The European Parliament and of the Council laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts COM/2021/206 final.

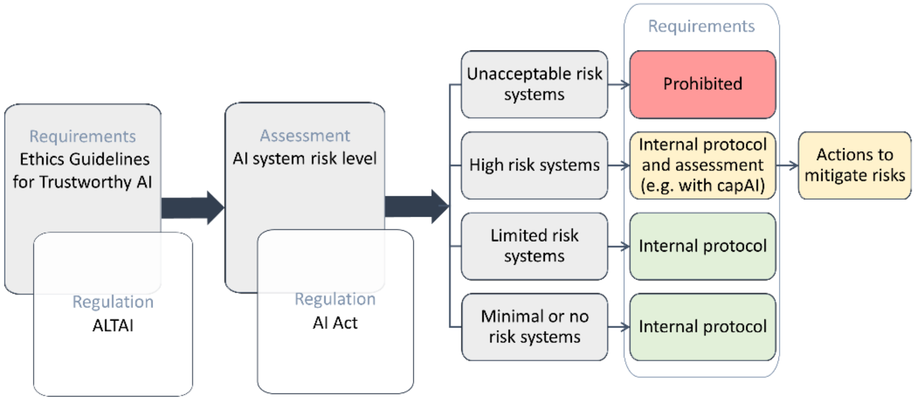


***Figure 5.*** *The EU trustworthiness framework for AI system providers*

**Ethics Guidelines for Trustworthy AI.** The third chapter of these guidelines establishes an assessment list that comprises the following seven key requirements of trustworthy AI systems. You may recognize several of these from previously described scientific standards.

1. Human agency and oversight
2. Technical robustness and safety
3. Privacy and data governance
4. Transparency
5. Diversity, non-discrimination, and fairness
6. Societal and environmental well-being
7. Accountability

Ensuring ongoing system quality means continuous reassessment of these ethics guidelines. To this end, the *Independent High-Level Expert Group on Artificial Intelligence*, which was set up by the European Commission, has created the specialized *Assessment List for*

*Trustworthy AI* (European Commission, 2020), which introduces proactive prevention of requirement violations.

**EU AI Act.** This is a framework for evaluating how much harm your systems might cause. Overall, it recognizes four categories of systems: a) *unacceptable risk systems* include real-time biometric systems (with a few exceptions for law enforcement purposes), social scoring algorithms, and AI that may involve manipulation risks, such as chatbots or deepfakes, b) *high-risk systems* are used for law enforcement, management of critical infrastructure, or recruitment, c) *limited risk systems* neither use personal data nor make any predictions influencing human beings, and include industrial applications in process control or predictive maintenance, *d) minimal or no risk systems,* such as AI-enabled video games or spam filters, are allowed free use. The European Commission expects most AI systems to fall into the category of limited risk systems (European Commission, 2023).

Given that unacceptable risk systems are outright banned, and that both limited and no risk systems do not require any action by providers, the weight falls on identifying and safeguarding high-risk systems. These require appropriate human oversight measures ("that cannot be overridden by the system itself and are responsive to the human operator, and that the natural persons to whom human oversight has been assigned have the necessary competence, training and authority to carry out that role") before being placed on the market or put into service[16].

The above-mentioned human oversight measures should be designed, assessed, and regularly reviewed by the system providers and, as a result, an assessment based on internal control would be efficient. In this direction, University of Oxford researchers provide the *capAI* tool

[16] *See:* Recital 48 of the EU AI Act.

(Floridi et al., 2022), which contains a procedure for assessing whether AI systems conform with the AI Act. Providers of high-risk systems can use this tool to demonstrate compliance while providers of low-risk systems can implement their commitment to voluntary codes of conduct. This tool consists of three components: a) an internal review protocol, which provides organizations with a tool for quality assurance and risk management, b) a summary datasheet to be submitted to the EU's future public database on high-risk AI systems in operation, and c) an external scorecard, which can also be made available to customers and other stakeholders (Floridi et al., 2022). Other tools can also assess and mitigate the risks of high-risk systems.

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