On some foundational aspects of human centered Artificial Intelligence

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Abstract. The burgeoning of AI has prompted recommendations that AI techniques should be “human-centered”. However, there is no clear definition of what is meant by Human Centered Artificial Intelligence, or for short, HCAI. This paper aims to improve this situation by addressing some foundational aspects of HCAI. To do so, we introduce the term HCAI agent to refer to any physical or software computational agent equipped with AI components and that interacts and/or collaborates with humans. This article identifies five main conceptual components that participate in an HCAI agent: Observations, Requirements, Actions, Explanations and Models. We see the notion of HCAI agent, together with its components and functions, as a way to bridge the technical and non-technical discussions on human-centered AI. In this paper, we focus our analysis on scenarios consisting of a single agent operating in dynamic environments in presence of humans.

1 Introduction

Recently artificial intelligence (AI) systems become popular and are playing an increasingly important and pervasive role in the life of individuals and society. The fact that AI systems can significatively affect human lives, and can play an active role in society, is fostering discussions on how these new systems should behave in their relationship with humans. Human Centered AI (HCAI) concerns the study of how present and future AI systems will interact with human lives in a mixed society composed of artificial and human agents, and how to keep the human into the focus in this mixed society. Due the interdisciplinarity of the topic, the discussion involves both technical and non technical people which see AI agents from different perspectives. It is often difficult to integrate these
perspectives in a coherent vision in which all points of view can contribute and complement each other. Of particular interests are the recent attempts to provide requirements and ethical guidelines that regulate HCAI systems, like the ones published by the European Commission in 2019 [11]. While such guidelines will certainly have an important impact on the future of AI, they typically describe HCAI systems at a very abstract, qualitative level. Understanding the concrete impact of such abstract requirements on the technical development of HCAI systems is neither trivial nor unique. A case in point is the recent European legislative proposal for an “AI Act” [5]. The necessity to define a precise grounding of high level qualitative statements into technical requirements for HCAI systems was explicitly noted in the above EC guidelines:

Requirements for Trustworthy AI should be “translated” into procedures and/or constraints on procedures, which should be anchored in the AI system’s architecture. [11, page 21].

The main objective of this document is to provide a reference description of an HCAI agent, together with its main components and functions, that helps to bridge the gap between the abstract specifications of HCAI systems provided by non-technical entities and the real implementation of these systems. Such a description is intended to contribute to the above grounding.

In other words, the main objective of this paper is an attempt to fill the gap between “non technical description of HCAI agent” and more “technical structure” that is understandable without a deep knowledge of the main techics of AI, such as Machine Learning, Automated Reasoning, Reinforcement Learning, Probabilistic inference and optimisation. Despite this, we will try to be precise enough to allow the mapping of high level concepts that one can find in the EC ethical guidelines into a more technical and technically operative description. Although the account of HCAI agents that we offer in this paper is certainly preliminary, we believe that it constitutes an important first step towards filling a crucial cultural gap.

The rest of this paper is organized as follows. In the next section, we provide a definition of HCAI agents in terms of their necessary features. In Section 3, we offer a schematic representation of a HCAI agent, and in Section 4, we discuss the key components of this representation. In Section 5, we look in more detail at one of these components, AI models. Finally, we discuss related work in Section 6 and draw some concluding remarks in Section 7.

2 Definition of HCAI agent

In the following, we provide a connotative definition of an HCAI agent by listing a set of features that an AI agent should meet in order to be considered Human Centered.

Agent-environment pair. We consider a reference framework composed of an autonomous agent that operates in an environment that includes the presence of
humans. We call this an agent-environment pair. HCAI concentrates on agent-environment pairs in which humans directly interact with the artificial agent in a collaborative attitude. We therefore exclude from our analysis situations in which the agent competes with humans, such as the ones recently studied in [6]. In an agent-environment pair, there is a clear separation between what is internal to the agent and what is external to the agent, i.e., the environment. At every time point in time, both the agent and the environment are in a state, that we refer as the state of the agent and the state of the environment, respectively. We don’t consider the level of quantum physics here, so we assume that both agents and environments are in one single state at every time. While the internal state of the agent is directly accessible to the agent, the state of the environment, including the humans that populate it, is not directly accessible by the agent. The agent can only partially perceive the state of the environment through observations.

The agent-environment pair can be represented as a pair \((\text{Ag}, \text{Env})\) with \(\text{Ag} = \{\text{State}(\text{Ag})_t\}_{t \geq t_0}\) and \(\text{Env} = \{\text{State}(\text{Env})_t\}_{t \geq t_0}\) where \(t_0\) is some starting time-point. \(\text{State}(\text{Ag})_t\) denotes the state of the agent at time \(t\), while \(\text{State}(\text{Env})_t\) denotes the state of the environment at time \(t\). We emphasize once again that the environment \(\text{Env}\) also includes the humans, and that these interact with the agent.

Observations and actions. The agent observes the environment via sensors, and acts upon the environment via effectors. Every interaction between the agent and the environment happens through these means. Observations and actions are considered here in a very broad sense. Sensors provide the agent with observations or percepts that range from low level data to natural language input, images, movies, and so on. Actions may range from physical actions such as moving ahead or grasping an object, to communicative actions (speech acts) such as displaying some data on the screen, uttering a sentence, smiling, or playing a song or a movie. We do not assume that there is a synchronisation between actions and observations, and both actions and observations can happen independently without following a precise protocol.

To be human-centered, an HCAI agent may have to comply to restrictions and requirements on the data that can be observed by an agent, and on the actions that can be executed. For instance, according to the EC Ethics Guidelines, observations in HCAI systems

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\text{[...]} \text{ must guarantee privacy and data protection throughout a system’s entire lifecycle. [11, page 17]}
\]

and should be unbiased. Concerning actions, the same guidelines postulate that they should be

\[
\text{[...]} \text{ consistent with the input, and that the decisions to execute an action are made in a way allowing validation of the underlying process. [11, page 22]}
\]
Furthermore, in the presence of an applicable legislation, an HCAI agent should execute only legal actions, i.e., actions complying with all applicable laws and regulations.

**Goal directed agents.** AI agents always have one or more goals to achieve. An agent’s goals can be codified in many different ways, depending on the architecture of the agent. For instance, the goal could be to optimize a certain function, to find the best path to achieve a position, to improve the agent’s capability of recognizing objects in a scene, or to correctly answer users queries.

To be human-centered, the achievement of such a goal by an HCAI agent should not harm the humans present in the environment. According to the principles of prevention of harm and fairness mentioned in the EU Ethics Guidelines:

> AI systems should neither cause nor exacerbate harm or otherwise adversely affect human beings, [...] ensuring that individuals and groups are free from unfair bias, discrimination and stigmatisation. If unfair biases can be avoided, AI systems could even increase societal fairness. [11, page 12]

Making explicit the goals of an HCAI agent in a necessary condition to support these principles. Furthermore an HCAI agent should not have goals that contrasts the goal of the human present in the environment.

**No full autonomy.** HCAI agent should not be completely autonomous, and their behaviour should always be sensitive to the external environmental or human context. Humans should always be allowed to intervene, e.g., to avoid that the agent performs a harmful actions, or a specific set of them. This is necessary to guarantee the principle of respect for human autonomy from the EU Ethics Guidelines [11, page 12], that allows a human to autonomously decide to prevent the execution of one or more actions to the HCAI agent. From an architectural point of view, this means that among the set of observations that an HCAI agent has to employ, there should be some that detect the willingness of the humans to interrupt some planned or executed actions.

### 3 Schema for an HCAI agent

Figure 1 shows a pictorial representation of our vision of an HCAI agent. This picture interprets literally the adjective “human centered” by drawing the human, and their environment, at the center of the representation surrounded by the agent. This is the opposite of the usual representation that shows an AI

So-called reflex agents [12], that directly map observations to actions, do not maintain an explicit internal representation of their goals. Most machine learning systems belong to this category. Even in this case, the mapping that implements the reflexes is programmed, or learned, with reference to some implicit objective that these agents are meant to achieve.
agent in the center, connected to the environment and the humans around it. A first observation concerns the fact that humans cannot be separated from the environment where they operate. Indeed they are part of the environment, and embedded in it. Humans and environment are complementary, interconnected, and interdependent in the natural world, and they interrelate to one another. Therefore HCAI Agents should take into account both humans and the environment where humans operate. In the picture this is represented by the blue and green Yin-Yang symbol in the inner ring.

![Diagram of a Human-Centered Artificial Intelligence Agent](image)

**Fig. 1.** A simple schematization of a Human-Centered Artificial Intelligence Agent (external ring). The agent interacts with of the humans (H) and environment (E) (inner ring) via the elements in the middle ring, relying on one or several internal models.

The outer ring in Figure 1 represents the artificial intelligent agent. For our discussion, the agent behaves as a unit. In many cases, however, the HCAI agent may be internally comprise several interrelated intelligent agents, which interact following, e.g., a multi-agent paradigm. The whole HCAI agent, or any of its component agents, accomplishes some task directly relevant for the humans it interacts with using one or several specific approaches, or models. For instance, an “artificial reasoner” could represent its knowledge in some logical formalism and support query answering and inference through automatic reasoning (e.g., SAT, ASP); an “artificial classifier” could be implemented in a deep neural network that is capable to classify images into different classes; and an “artificial planner” can produce plans and take decision exploiting classical planning techniques or reinforcement learning. To solve complex tasks, different systems and methodologies typically need to be integrated. A black box integration of each
“intelligent agent” is not sufficient; it is necessary to integrate and make all these different approaches to collaborate one another in a glass-box method. We shall come back to this point when discussing hybrid models in Section 5.1.

The middle ring represents the interaction between the human-environment system and the (integrated) artificial intelligent system. The type of interactions that one can see between human-environment system and the artificial agent happens across a set of artifacts that are “shared” by the human-environment and the artificial systems. We briefly introduce them here, and we shall describe them more extensively in the rest of this document. Dependability Requirements are artifacts, produced by humans, that specify the expected behaviour or other non-functional properties of the artificial intelligent system. Actions are considered in a broad sense. They represent the actions that the artificial agent can perform on the human-environment system, as well as the action that the human can perform on the artificial agent. These can be physical actions, that affect the state of the environment, or informative actions, that affect the knowledge of the human or of the artificial agent. Observations are all the data that the artificial intelligent system can collect through its sensors. Finally, Explanations are artifacts produced by an artificial agent that “explain” to the human the reasons of its behaviour, e.g., the reason why it took a decision or executed an action. Explanations should be human understandable and acceptable in a rational system shared by the machine and the human.

4 Key components of an HCAI agent

Figure 1 identifies five key components that constitute a Human Centered AI agent: four types of artifacts that are shared by the human-environment system and the agent and that mediate the interactions between them; and a set of internal models. We now discuss these components in greater detail.

4.1 Observations

An agent can observe the humans and the environment through its sensors. Here we use sensor in a broad sense, i.e., everything that can be used by the agent to autonomously acquire data about the environment (including humans) and everything the humans and the environment can use to synchronously or asynchronously input data to the artificial agent. Among the observations we also include the “commands/requests” that humans pose to the artificial agent.

There is a great variety of types of sensors, and they all serve their purpose depending on the information which they are meant to collect, and on the application domain. For example, sensors in Internet of Things applications may include cameras, ultrasonic, infrared, acoustic, mechanical, and so on. In Robotics applications, sensors may include potentiometers, accelerometers, Gimbles, lidar, an so on. In Media applications, sensors may include digital cameras, audio recording, textual documents, and so on. Essentially, sensor systems inject input data. These can come in streams, mostly for online systems, or in batch,
mostly for offline systems. The way input data is represented varies widely, from continuous to discrete, structured, lists, trees, and so on. Input data are typically coupled with some meta information that describes their representation and structure. In general, every item of data is associated with one or several time stamps, that can be relative or absolute.

**Definition 1.** The observations of an HCAI agent are all the data that an agent can acquire through its sensors. We denote by $\text{Obs}_{\leq t} = \{\text{Obs}_{t'}\}_{t \leq t' \leq t}$ the observations about the human-environment system that are available to the agent at a given time $t$. $\text{Obs}_t$ may or may not be a function of the state of the environment and the agent at time $t$. In general, we state that

$$\text{Obs}_t \sim \text{Pr}(\cdot \mid \text{State(Env)}_t, \text{State(Ag)}_t),$$

i.e., observations at time $t$ follow some (possibly unknown) probability distribution conditioned by the state of the environment and of the agent at time $t$.

### 4.2 Actions

The set of actions of an agent are all the possible ways that the agent has to affect the state of the environment and of the humans which it interacts with. Actions can be *physical actions*, e.g., robot moves forward 10 cm, an autonomous car brakes, an autonomous personal assistant books a room in hotel Bellavista or buys 100 stocks of the company SuperGulp. Another type of action are *informative actions* that provide information to the human as a consequence of a decision that the agent has reached. Examples of informative actions are the communication of the result of a classifications of an item provided in input, or the communication that the price of SuperGulp stocks is falling.

Actions should produce a tangible effect on the environment and/or the humans in it. This means that if execution does not fail, the state of the humans or environment once an action is terminated should be different from their state before the execution of that action. Note that an internal agent activity, like an agent taking a decision about doing something, should not be considered as an action, because it changes only the internal state of the agent but it does not affect the environment. The real action consists on the effective execution of the decision. Also note that in general the outcome of an action is not deterministic.

Concrete examples of actions include the following. If an agent’s task is to classify documents in $n$ classes, its actions are those that communicate the result of the classification of an item into one or more class. Such action will change the knowledge state of the human that has requested the classification. Classification without communication should not be considered as action. Clearly all the actions of a robot involving physical movement are considered as actions since they change the position of the robot in the environment. The set of actions associated to an artificial agent can be discrete or continuous. Notice that the set of agent’s actions does not include the actions that are executed by the humans, or other events that can happen asynchronously in the environment.
Definition 2. The actions of an HCAI agent is a set $\mathcal{A}$ such that any $a \in \mathcal{A}$ is associated to a set of effects $\text{Eff}(a)$ which describes a transformation of the state of the environment that is directly relevant for the humans in the environment. The mapping $\text{Eff}(a)$ can be deterministic, non deterministic or probabilistic.

An important aspect of the above definition is that actions in an HCAI should be directly relevant for the humans that populates the environment. This aspect relies on the pre-theoretical notion of relevance that cannot be easily captured in a formal definition, since relevance may emerge through complex causal chains. In some cases, relevance is clear: the decision of an agent to grant a mortgage to a human is definitively relevant for the human; while the decision taken by a system that controls the trajectory of a satellite cannot be considered human centered, although it might have an impact on TV viewers. Most cases, however, are not so clear cut. For instance, a domestic robot’s plugging to the charging station may not directly affect the state of a human; but if this action consumes the solar-powered battery cells of the home, this may affect the ability of the human inhabitant to cook dinner later on.

4.3 Explanations

An explanation is an explanation of some decision. In HCAI, explanations are meant to explain to a human, or a set of humans, the decision of executing an action $a$ made by an agent at time $t$ when it was in the state $\text{State}(\text{Ag})_t$. As argued in [9], the definition of explanations for a decision taken by an HCAI agent cannot be provided without making explicit reference to the human to whom the explanation is addressed, i.e, the explanee. In general, an explanation of a decision taken by the agent can be independent from how the agent reaches such a decision. This is especially true when the decision is taken by a black-box method such as a neural network.

Definition 3 (Explanation). An explanation of an HCAI is a representation of the reason why the agent took a decision to execute a given action $a$ in state $\text{State}(\text{Ag})_t$. Such an explanation should be intelligible, understandable and acceptable by the explanee.

This definition sees explanation as an artifact. Another notion of explanation is to see it as the process of building or communicating an explanation. There is a rich literature in which explanation refers to a dialogue, and therefore a collaborative process, between the human and the agent, where the human collaborates with the agent in the creation of an explanation of the agent’s decision that is satisfactory for the human. The result of this process is an explanation artifact that can be stored and reused.

4.4 Requirements

A requirement, including the concept of dependability requirement, is the formulation of a functional need that an AI system must satisfy. This is central
to the problem of verifiable AI, which has the objective of checking that a system meets its requirements, including functional specifications and dependability attributes. Dependability requirements should be expressed in a human understandable way: in fact, they are usually formulated by humans. The problem of verifiable AI is how to translate these requirements in algorithms that check that the system is compliant with them. Being a human produced artifact, providing a sharp definition of a requirement is rather complex if not impossible.

Some requirements may be specified in a formal language, that has an intuitive semantics for the human, so that it is possible to verify automatically that the artificial intelligent system behaves according to the requirement, at least to some measurable degree of certainty. Some requirements may not be expressed in a formal language, as representing them in a mathematical structure is still an open issue. Below, we concentrate on formal requirements.

**Definition 4.** A formal requirement is an expression in a formal language (e.g., in mathematics or logics) that unambiguously describes a criterion to determine if an agent-environment pair fulfils it.

There are aspects of the verification of requirements for HCAI agents that go beyond standard requirement engineering, and that stem from these being AI agents as opposed to more traditional software systems. In particular, AI agents have the ability to learn new knowledge by generalising observations done on a set of data, and to make inferences from the learned knowledge in order to take decision in previously unseen or unmodeled situations.

In addition, in Human-Centered AI agents one may need to impose requirements on how the agent reaches the decision that leads to a certain behaviour. For instance, in the case of an agent that contains machine learning models trained on data, typical requirements concerns the fact that these data are not biased, or that they respect the GDPR. This type of requirements goes beyond the above definition, that focuses on the behaviour of the agent relative to the environment in which it operates.

4.5 **Models**

An HCAI agent takes decisions on how to act in the environment, or how to react to some input coming from the humans and/or the environment, on the basis of one or more models of the human-environment system which it is interacting with. Models are abstract (computational) structures that allow to answer queries about what holds in the current or past situations, and to predict what will be true in the future. Models can also be used to simulate possible alternative evolutions of the human-environment system in order to take the “right” decision now.

HCAI agents are equipped with a set of models that represent the knowledge of the agent about the human-environment system. This knowledge is used to support the agent in making decisions about which actions to perform. In general, we cannot assume that such models are correct, i.e., that their reflect the true
state human-environment system and that their predictions are effectively true. For this reason it is more appropriate to speak about belief instead of knowledge. Neither we can assume that models are complete, i.e., that they describe the environment in all its details. Indeed they are simplified, abstract representations of some aspect of the environment obtained by abstracting away irrelevant (or believed to be irrelevant) details. Even at the given level of abstraction, models may still miss information if this is not known or observed.

5 Models for an HCAI agent

The core knowledge of an HCAI agent is encapsulated in the set of models that it adopts in order to interpret the input data, take decisions, and provide explanations for the decisions taken. If we ignore the physical aspects of an agent, it is acceptable to say that the behaviour of an HCAI agent is fully determined by its models. Most of the requirements and guidelines provided for HCAI agents thus concern how models are built, how they evolve, and how they are used to take decisions.

Given this central role of models, it is useful to discuss in more detail what are the different classes of models that we can use in an HCAI agent, and how these models are built and how they evolve — in other words, the life-cycle of models. The rest of this section is devoted to these topics.

5.1 Classes of AI Models

Providing a complete and coherent classification, or even an ontology, of AI models is beyond the scope of this paper. For our purposes, it is enough to list the most important, general classes of AI models. In our classification we take a “technological” perspective, i.e., we define classes on the basis of the set of methodologies which are used to specify the model, to represent information, and to perform decisions. We identify four main classes plus their combination.

Logical Models. The key aspects of the environment and the human are represented with a logical theory (set of formulas of a logical/formal language) and decision on the basis of this model are taken via logical reasoning. Examples of this type of model are Logical Knowledge Bases and Ontologies, Logic programs, and planning domains specified via PDDL or other action languages. Logical models are specified declaratively using a set of terms and formulas from a logic based language. A good summary of many different logical models is provided in the Handbook of Knowledge Representation [8]. Logical models provide information of what is true, what is false and what logically follows from some premises. Minker [10] offers an overview of how logical models can be built and how they can be used for inference, decision making and planning.
Probabilistic Models. The key aspects of the environment and the human are represented by some probabilistic distribution. Decision are taken on the basis of probabilistic inference. In an AI model, probability distributions are not simply defined over a set of hypotheses but rather over some more complex structure suitable to represent knowledge, as noted by Chater et al [1]:

The knowledge and beliefs of cognitive agents are modeled using probability distributions defined over structured systems of representation, such as graphs, generative grammars, or predicate logic. This development is crucial for making probabilistic models relevant to cognitive science, where structured representations are frequently viewed as theoretically central.

Examples of this type of models are statistical graphical models, like Bayesian Networks and Hidden Markov Models. Usually probabilistic models distinguish between observable variables, which correspond to the evidence that an agent is able to observe directly, and hidden variables, whose distribution should be discovered from the data. The key concept in this type of model is the variable assignment, i.e., an assignment to all the random variables, on which it is possible to apply the model in order to predict the likelihood of such an assignment. Beside probability, other mathematical theories have been used to build models for uncertain knowledge and plausible reasoning, including possibility theory [4] and belief function [16]. We extend the term “probabilistic models” to cover models based on those theories as well.

Real-Valued Functional Models. The key aspects of the worlds and the user are represented through (a set of) real-valued functions. These models can be used take in input observable quantities and produce an estimation of some non-observable quantity, or predictions of future values. Examples of this type of models are linear models, support vector machines, decision trees, random forest and (deep) neural networks.

A large class of real-valued functional models is constituted by neural network models. A neural model is a directed graph of nodes. Each node is associated with a non linear activation function, the input of a node \( n \) is a linear combination of the outputs of the functions associated to nodes that precede \( n \) in the graph. Both the linear combination and the activation function are associated with a set of parameters, that need to be instantiated in order to fully define the function. A neural network model is also associated to a Loss (or Cost) function, that determines the approximation error (i.e., difference between known and predicted outputs) to be minimized.

For every instantiation of its parameters, a neural network computes a function \( f : \mathbb{R}^k \rightarrow \mathbb{R}^h \) where \( k \) is the number of input nodes (i.e., nodes that don’t have any predecessor) and \( h \) is the number of output nodes (i.e., nodes which are not predecessor of any other node). Like in all machine learning models, the main objective in a neural network is to find an instantiation of the parameters that minimizes the Loss/Cost function.
Dynamic Decision Models  The main purpose of these models is to represent the dynamics of the environment in terms of states and relations (transitions) between states, as well as the payoff obtained by the agent’s being at a state. A state represents what holds at a given time point in the environment; two states are connected by a transition if the agent can pass from one state to the other by executing an action. Furthermore every state is associated with some “evaluation” function that expresses how much that state satisfies the objectives of the agent. These models are used by the agent to decide which actions to take at every future state in order to maximize the likelihood of its payoff. These models are associated with a set of algorithms that allow the agent to produce a “policy” or a “plan”, i.e., a sequence of actions, or some more complex control structure, that will reach a state with optimal (or sub-optimal) payoff. This class includes a vast variety of models, such as (Partially Observable) Markov Decision Models, Planning Models, and Finite Automata.

Hybrid models. In many cases a model presents characteristics that are common to more than one of the classes described above. We call them hybrid models. Hybrid models are models that integrate some of the previous types of models. Examples of such models are approaches that integrates logical and numerical models (e.g., Logic Tensor Networks, Lyrics) approaches that integrate logical and statistical models (e.g., Markov Logic Networks, Probabilistic Logic Programming), and approaches that integrate numeric, statistical and logical models (e.g., DeepProbLog, deep probabilistic logic programming, and Probabilistic Soft Logic).

5.2 The lifecycle of HCAI models

We represent the lifecycle of each model in an HCAI agent as illustrated in Figure 2. Below, we describe each main step in this cycle.

Model schema specification  A model schema describes a class of models that share the same structure. The models within the same class can be obtained by instantiating a (possibly infinite) set of parameters of the model schema. Notice that here we use the term parameter in a broad sense, referring both to the parameters of a probabilistic model, or a neural network, but also to the signature of a logical language. The model schema specification is usually done manually, but there is a growing interest in the community in developing methods that (semi-)automatically learn the model structure from data: examples include structural machine learning, programm synthesis, non-parametric statistical models, auto-generated neural networks, predicate invention, and learning planning domains.

Associated to a model schema there is also an “intuitive explanation” of parts of the model. For instance, in choosing a logical language to specify the knowledge of an agent one has to say for some of the predicates what is the intuitive meaning (with respect to states of the environment, i.e., the proposition)
that those predicates. Similarly, in a neural network for classifying images in N classes $C_1, \ldots, C_N$, one has to say which of the output neuron corresponds to each class $C_i$.

**Model instance specification/learning/update** The instantiation of a model schema amounts in setting the parameters of the model. This amounts in encoding a certain amount of knowledge about the environment utilizing the “tool-set” provided by the model schema. The encoding can be done manually, as it often happens in logical rule based models via some knowledge engineering activity, or via supervised learning from data manually labelled by humans, or in a fully unsupervised and automatic manner (e.g., clustering). Statistical models can be obtained by Bayesian inference from a set of observations or by Maximum likelihood, or maximum a posteriori inference. Other methods to model specifications can also be obtained by model adaptation or transfer learning. Similarly, updating the model can be performed automatically via retraining, or manually by modifying the parameters. Automatic learning of facts and rules from natural language is also possible. Methods for automatic learning of constraints from data are also available.
Inference with the model The second important aspect is how the model is used to infer a decision, i.e., an action that the artificial agent decides to undertake. Given a set of observations \( O \) as input, the model provides as output a set of actions or a policy for actions. This is obtained by applying an *inference engine* which is defined on the model.

In this phase the model instance is queried about what holds in the environment. Inference can be very simple, like in neural network (simple forward propagation) or rather complex, like in constraint satisfaction where it may be necessary to apply search or optimization algorithms. In logical models inference is done via some form of logical reasoning (e.g., satisfiability) or model checking, while in statistical models inference can be a generative process (generate a data that has certain properties) or to compute some marginal distribution of a certain (set of) stochastic variables. What all the above inference activities have in common is that they don’t change the model, but only query it.

Quality Control and Maintenance Once an AI artifact is ready to be used in practice, additional tasks that are often not part of research activities become important to reach higher Technology Readiness Levels.

For certification purposes and for the permission to use the artifact in practice on/with non-expert users, *testing and verification* procedures for safety/security-related properties of the behavior of the model can be necessary. For products that are already in usage and needs to be updated, *maintenance and updating* methods need to exist so that problems that are identified after shipping the model can be counteracted. For supporting users and for legal reasons, it can be necessary to have powerful methods for *debugging* model properties and (re-)actions, and for *explaining* why certain outputs were (or were not) generated. Moreover, in connection with updates of the model, these methods can be useful to prove to authorities that certain behavior is excluded in the future.

This part of the AI artifact lifecycle is very relevant to human-centric artificial intelligence, because it is the longest-lasting process in the existence of the model where the model has contact with a large number of untrained human individuals and unseen input data.

6 Related work

With the increasing prominence of AI, there is an increasing reflection on what it means for AI to be “human-centered” and several papers have been published on this topic, some of which are discussed below. To the best of our knowledge, however, the work reported here is the first one that tries to take a foundational approach to the problem of human-centered AI, framing the discussion in technical terms by defining the notion of a human-centered AI agent.

Wei Xu [15] emphasizes that human centered AI systems should exhibit behaviour which is intuitive for humans, and that this can be achieved by adopting human centered design. The paper proposes an architecture that supports
the collaboration between humans and machines by considering three main factors: *ethically aligned design*, necessary to create AI agents that behave fairly, and collaborate with humans rather than competing with them; *resemblance of human intelligence*, necessary to develop AI agents with human-like intelligent behaviours; and *comprehensibility, usefulness and usability*, necessary to develop AI agents that are capable of helping humans.

Ben Shneiderman \[13\] suggests that making human-centered AI systems requires the combination of AI-based intelligent algorithms with human-centered design. The author highlights that, in developing HCAI, one should not limit the evaluation to performance to the technological parts, but higher attention to human users and other stakeholders. This requires an increased prominence of user experience design and of human performance measures. The perspective taken in the paper is to support the 17 United Nations Sustainable Development Goals.\[2\] This work resonates with the AI model lifecycle proposed here (see Section 5), especially in the parts of providing input for requirement specification and of collecting the agent feedback.

In another work \[14\], Shneiderman stresses that HCAI systems should give humans a greater control on the ever-increasing automation, instead of replacing them in the decision processes. According to the author,

> [...] humans must have *meaningful control of technology* and are responsible for the outcomes of their actions. When humans depend on automation to get their work done, they must be able to anticipate what happens, because they, not the machines, are responsible.

Shneiderman’s stance is important, as it poses a limit on the decision power of the machines and it relieves them from any responsibility. Such a vision clashes with an opposite request of AI systems to be increasingly autonomous.

The tension between machine autonomy and human control gave rise recently to a field called *Human Centered Machine Learning*, which focuses on the development of HCAI systems that adopt models that can be trained via machine learning techniques. See Kaluarachchi *et al* \[7\] for a review of the recent literature. The main objective here is to develop AI models that take into account the input provided by humans when they get to a decision. An example is provided by Abir Deet *et al* \[2\], who propose a model that classifies images while allowing user input during inference. An empirical evaluation shows that this model can surpass the performance of models trained for full automation, as well as the one of humans operating alone.

Dignum and Dignum \[3\] argue that human-centered AI involves a shift from an AI which is able to solve human tasks that require some form of intelligence, to an AI which is aware on the social environment in which it is embedded, and operates taking into account all the limitations, the opportunities, and the needs of the social environment. This position suggests that an AI system should be considered as part of a broader socio-technical system. As they put it:
AI systems are fundamentally socio-technical, including the social context where it is developed, used, and acted upon, with its variety of stakeholders, institutions, cultures, norms and spaces.

This perspective is in accordance with the schema of a human centered AI agent proposed here (see Figure 1), where the AI agent is built around the environment, and, in some sense, also includes the social context in which it operates.

7 Conclusions

Human-centered AI agents are considered as part of a larger system that also includes the humans, their society and the environment at large. Consequently, the developments of HCAI agents is not only a matter of developing efficient and effective algorithms to solve complex problems that require some form of intelligence. HCAI looks at the developments of AI focussing also on human values such ethical principles, fairness, transparency of decision and objectives, . . . . As such, human-centered AI is an intrinsically multi-disciplinary effort that requires the establishment of a common ground between technical and non-technical disciplines such as, sociology, law, ethics, and philosophy. This paper is an attempt to offers a first step in fulfilling this requirement, by introducing the general concept of a Human-Centered AI agent, together with its main components and functions, as a way to bridge technical and non-technical discussions on human-centered AI.

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