DATA POLLUTION & POWER

WHITE PAPER FOR A GLOBAL SUSTAINABLE DEVELOPMENT AGENDA ON AI

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White Paper for a Global Sustainable Development Agenda on AI

Gry Hasselbalch

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Abstract

This white paper explores 'data pollution' as the adverse environmental impact of the data of artificial intelligence (AI). It frames the environmental problems of AI and big data in the context of powers and interests, explores eight data pollution domains, and provides a set of questions that may be further explored when including data pollution in the global sustainable development agenda.

The first chapter outlines shared terminology that can be used to address the data pollution of AI and its contextual interrelated power dynamics. The second chapter describes the current geopolitical landscape of AI ethics and sustainability. The third chapter explores eight key domains of the natural, social and personal environment in which data pollution has the greatest impact: Nature, Science & Innovation, Democracy, Human Rights, Infrastructure, Decision-Making, Global Opportunities, and Time. Lastly, in the fourth chapter, a set of questions for the global sustainable development agenda are presented.

About the Data Pollution & Power Initiative (the DPP Initiative)

The Data Pollution & Power initiative was set up by Gry Hasselbalch (the author of this paper) at the Sustainable AI Lab at the Institute of Science and Ethics (IWE), Bonn University to explore the power dynamics that shape AI data pollution across the UN Sustainable Development Goals (SDGs). The project examines how power dynamics and interests in AI data determine the handling and distribution of data in data ecosystems and considers actions and governance approaches that are intrinsically interrelated in systems of power and interests.[1]

About the Data Pollution & Power Group (the DPP Group)

The Data Pollution & Power Group is a group of experts that was established in June 2021 to examine the data of AI as a human and natural resource in 'eco systems' and environments—and 'data pollution' as the interrelated (big) data deriving from AI which has adverse effects on the Sustainable Development Goals (SDGs). It is a cross-disciplinary group with diverse expertise and interests that cut across several of the SDGs. The core aim of the group is to debate, scope out, map and explore the data pollution of AI.

About the Sustainable AI Lab

The Sustainable AI Lab[2] is an initiative of Professor Dr Aimee van Wynsberghe, Director of the Institute of Science and Ethics at Bonn University, and the result of her Humboldt Professorship for the Applied Ethics of AI, which was awarded by the Alexander von Humboldt Foundation.[3]

The Sustainable AI Lab brings together researchers from various backgrounds to conduct projects aimed at: measuring & assessing the environmental impact of AI, ways of making AI systems more sustainable, and directing AI towards the SDGs.

WHITE PAPER GLOSSARY

Agency

In this white paper, 'agency' does not imply autonomous individual agent agency in human or technical form. Instead, it is used to refer to socio-technical processes and systems that consist of a complex of actors and components that in combination constitute various actions (such as e.g. making 'decisions', 'infrastructuring' (as a verb), 'discriminating' or 'polluting') and that have an identifiable impact in their respective environments. These 'socio-technical actions' are driven forward by dominant interests and cultural narratives that are reinforced in socio-technical design. They are realised in more or less humanly controlled contexts with different levels of human involvement.

Autonomous Decision-Making (ADM) Systems

ADM systems are autonomous or semi-autonomous (AI) decision-making systems. ADM systems are embedded in the socio-technical information infrastructure of private and public decision-making sectors; decisions are increasingly informed or replaced by big data AI systems that predict and analyse risks or potential based on accumulated data.

Big Data Socio-Technical Infrastructures (BDSTIs)

BDSTIs are socio-technical infrastructures constituted by big data technologies.[4] They are the primary infrastructures of global information economies and societies and are institutionalised in systems requirements standards for ICT practices and in regulatory frameworks, and they are invested with human imagination about the challenges and opportunities of big data.

Artificial Intelligence Socio-Technical Infrastructures (AISTIs)

AISTIs are an evolution of the analytical capabilities of BDSTIs.[5] They are BDSTIs designed to sense their environment in real time, learning and evolving with autonomous or semiautonomous 'agency' (see above). BDSTIs extend space in digital data and AISTIs work in time by acting on that data to form the past and present in the image of the future.

Data Ethics of Power

Data Ethics of Power is an applied ethics approach concerned with making the power dynamics of the big data society and the conditions of their negotiation visible in order to point to design, business, policy, and social and cultural processes that support a human(-centric) distribution of power.[6]

Data Interests

A 'data interest' constitutes a specific need, value or goal centred on data as a resource.7 This can be political, commercial, or scientific interests in data or an individual's interest in protecting or making use of their personal data. Data interests can be found in data design and in data governance activities. (see also 'agency' above)

Data Pollution

Data pollution is the interrelated adverse impact that the generation, storing, handling and processing of digital data has on our natural environment, social environment and personal environment. It is the unsustainable handling, distribution and generation of data resources. Data pollution due diligence means managing—in organisational, policy and design practice—the adverse effects and risks of data exhaust on natural, social and personal ecosystems.

Data Pollution Domains

This white paper identifies and explores the most prevalent and urgent data pollution problems and challenges in a catalogue of eight domains within the natural, social and personal environments: *Nature, Science & Innovation, Democracy, Human Rights, Infrastructure, Decision-Making, Global Opportunities, and Time*. These domains are explored in terms of the material and immaterial power conditions and contexts that are affected by data pollution.

Environmentally Sound Technologies (ESTs)

Environmentally sound technologies protect the environment, are less polluting, use all resources in a more sustainable manner, recycle more of their wastes and products, and handle residual waste in a more acceptable manner than the technologies for which they were substitutes...[8]

International Human Rights

International human rights have their origin in the UN Declaration of Human Rights (UNDHR), which was drafted by representatives from regions worldwide and adopted in 1948, and has been expanded upon via other international instruments, treaties and covenants. Furthermore, the European Convention on Human Rights (ECHR) was signed by 47 member states and entered into force in 1953. Mechanisms are in place for monitoring the compliance of states party to the UNDHR, while member states that have signed the ECHR are accountable to the European Court of Human Rights (ECtHR). In the EU, the Charter of Fundamental Rights, which came into force in 2009, further embeds the rights of EU citizens into EU law. Here, the protection of personal data (article 8) as a fundamental right of EU citizens is delineated, for example, in an extensive data protection regulatory framework (the GDPR).

Infrastructure

Infrastructure is the immaterial and material socio-technical organisation of space. It constitutes social, cultural and spatial architecture that is created and directed by humans in social, economic, political and historical contexts. Socio-technical infrastructures are human-made spaces composed of engineered and non-engineered processes that evolve in contexts of negotiation and struggle between different societal interests and aspirations.[9]

The Human-Centric Approach to AI

The human-centric approach to AI concerns the ethical responsibility of humans and the preservation of human dynamic qualities and empowerment in socio-technical AI infrastructures. The approach gained momentum in the late 2010s in global policy discourses on AI as a human rights and risk-based approach of the EU's Artificial Intelligence strategies and policy instruments and the ethics recommendations and principles of intergovernmental organisations, such as the OECD and UNESCO.[10]

Socio-technical

Society and technology are intrinsically interlinked and cannot be understood in isolation. Society is part of technology and technology is part of society. Technology design is a complex process constituted by diverse social, political, economic, cultural and technological factors.[11]

Sustainable Development Goals (SDGs)

The 17 Sustainable Development Goals (SDGs) of the UN's 2030 Agenda address the balance of three dimensions of sustainable development—economic, social and environmental—with strategies to undertake climate change, improve health and education, reduce inequality, and stimulate economic growth.

INTRODUCTION
Data Pollution & Power

DATA POLLUTION IS TO the big data age what smog was to the industrial age. Our response to data pollution will develop much like our reaction to traditional forms of pollution—just much faster and hopefully with dedication and great force. Only a few decades ago, a 'nice' automobile was big, and its toxic exhaust a distant ghost in a dark sky accumulating over cities. In contrast, today's automobiles are required to adhere to legal regulations and the market demands environmental standards and friendliness. We have environmental laws, standards for sustainable business conduct, and awareness of air, water and land pollution. These risk mitigation strategies and social responses have evolved alongside a growing number of scientific studies and tools measuring the adverse impacts of harmful pollutants on our natural environments. An environmental movement to tackle the pollutants of the Industrial age has matured and materialised in law, policy, international agreements, consumer demands, innovation and business practices.

It is time now for an environmental movement to tackle the data pollution of the big data era.

In 1972, the urgency of global political attention and coordination on environmental issues was recognised at the Conference on the Human Environment in Stockholm, Sweden. This was also where 'Environmentally Sound Technologies' (ESTs) were defined as technologies capable of reducing environmental damage, while at the same time being designed for sustainability during implementation and adoption.[12] Echoing these early ideas about the role of human science and technology in tackling environmental challenges with a global coordinated sustainable approach, **this white paper places data pollution as part of a global sustainable development agenda in relation to AI. It addresses a largely undefined and inconsistently studied area of environmental concern: data pollution caused by specific AI technologies.** Based on desk research, the author's active participation in the emerging global AI governance and policy field, and invaluable interactions with a group of experts, the Data Pollution & Power Group hosted by the Sustainable AI Lab of Bonn University, this white paper conceptualises and presents a preliminary outline of the interrelated components of data pollution and the power dynamics that challenge our societal response to this environmental problem.

Technological tools with AI capabilities can help tackle some of the biggest challenges identified within the sustainable development agenda. For example, AI can help in the green transition with policy foresight, prediction of environmental impacts, more efficient use of limited resources and optimisation of production processes. However, we need to ensure that the original reflections on the sustainability of the technologies we develop and deploy today are not overshadowed by AI hype, power struggles and competition. **AI data pollution comes in many forms, from the carbon footprint of processing and storing the data used to train AI systems to non-**

representative big data sets and biased healthcare analysis, or invisible data micro-targeting that pollutes democratic electoral processes. Awareness of the various forms of the data pollution of the big data age calls for a proactive approach to the technologies we build, govern and embed in our socio-technical infrastructures.

Public awareness of data pollution in society and among the companies and institutions responsible for it today lags behind other environmental concerns. We therefore urgently need to develop and increase awareness about it. However, to do so, a conceptual framework is needed to address the power dynamics that shape the conditions of data pollution. **Data pollution constitutes an unsustainable distribution and exploitation of data resources.** In a big data economy, data is the main 'currency' and 'resource', and therefore also the locus of different societal interests and power dynamics that do not always put human, social or environmental interests first. As a result, data resources are distributed unevenly and exhausted while creating imbalances in delicate personal, social and natural eco-systems.

This white paper explores the power dynamics that are transformed, impacted and even produced by data in our natural, social and personal environments. The transformation of the power (im)balances between different actors on a local, regional and global scale is at the heart of the matter. In modern democracies, power asymmetries are breathing data pollution. On a global scale, data pollution is an environmental problem constituted by and further contributing to imbalances in ecosystems of power. Data pollution is a human condition and creation that underpins new modes of technological colonialism—AI, digital and data colonialism—which impacts global opportunities, democratic participation, and the very constitution of democracy.

An important note and caveat on the voice, the 'we', of the white paper: although the focus is global, the point of departure is mainly a European context, based on the embedded experience and perspective of the author. This means that although the white paper does address the core structural power dimension of the global data pollution problem, it does not claim to speak with the experience and voice of those who are most exposed to data pollution. It also means that there is an underlying emphasis on European policies and regulations on data protection, AI and platforms.

This white paper attempts to make visible the connections between the different actors and components of a nascent data pollution environmental movement, with 'sustainability' as the thread that links the elements of the movement in shared understanding and a common approach. Data pollution is conceptualised holistically as the interrelated adverse effects on the ecosystems of our natural, social and personal environments, and a first attempt is made to highlight the power dynamics that shape our identification of data pollution and societal responses to it.

This white paper has three objectives:

1. **Shared Terminology**

The first objective is to delineate common ground for debate on data pollution by outlining shared terminology that can be used to address the data pollution of AI and its contextual interrelated power dynamics.
The aim is to frame the negative effects of AI data in the context of sustainable development, and place data pollution as a problem on par with other environmental issues. As a point of departure, data

pollution is therefore described here in terms of the entire field of the environmental impact of AI data, from the carbon footprint of AI-related energy consumption to privacy implications for individuals. Furthermore, terminology for an approach to data pollution which aims to make visible and tackle the societal power dynamics of powerful actors, hierarchies and asymmetries is delineated.

2. **A Catalogue of Power Domains Impacted by Data Pollution**

The second objective is to explore the key domains of the natural, social and personal environments in which data pollution has the greatest impact. To create common ground for the debate surrounding data pollution with a focus on the power dynamics that shape the field, this white paper identifies and explores the most prevalent and urgent data pollution problems in a catalogue of eight domains of our natural, social and personal environments: *Nature, Science & Innovation, Democracy, Human Rights, Infrastructures, Decision-Making, Global Opportunities, and Time*. These domains are explored in terms of the material and immaterial power conditions and contexts that are impacted by data pollution.

3. **Making Power Dynamics Visible**

The third objective is to make the power dynamics that shape data pollution visible by repositioning big data and AI as environmental risks. In the last section of this white paper, a set of questions are posed to open up the discussion about different aspects of data pollution in different domains and among various power actors. The questions were drafted by the members of the Data Pollution and Power Group and edited by the author.

1.

DATA POLLUTION TERMINOLOGY

THERE IS A TENDENCY to reduce the complexity of sociotechnical change in disciplinary and sectoral silos and specific stakeholder interests. However, complex interrelated environments know no boundaries and, as such, a lack of coordination and translation between various fields of expertise, stakeholder groups and interests can limit the mitigation of the adverse environmental impacts of data pollution. We need shared terminology and a conceptual platform from which to pose the most urgent data pollution questions to be addressed within the global sustainable development agenda.

As a concept in policy and business discourse, sustainability has been articulated over the last five decades alongside the identification of the adverse impacts of the Industrial Age on social, economic and natural environments. From the outset, it has represented a more holistic approach to the management of environmental risks and impacts.[13] It includes the recognition that global environmental problems are largely the result of the unsustainable consumption and production patterns of the Global North, coupled with widespread poverty in the Global South.[14]

The potential of AI and big data technologies to tackle traditional environmental challenges and reach Green Deal (EU) or Sustainable Development (UN) goals has been explored extensively and is time and again highlighted in AI and data policies. The sustainability of AI and big data, on the other hand, is predominantly treated as a separate field of action in policy as well as scientific research. Here, we want to, as van Wynsberghe describes it, treat sustainability *for* and *of* AI data as two sides of the same coin.[15] That is: we need to recognise that AI cannot help us reach sustainable development goals if it itself is unsustainable.

We will herein explore data pollution in the context of the development of AI technologies and the creation of Artificial Intelligence Socio-Technical Infrastructures (AISTIs) in particular.[16] Big data is the key resource of the big data society and Big Data Socio-Technical Infrastructures (BDSTIs),[17] but it is an empty one without complex data processing systems for analysis. Today, in the early 2020s, AI systems give meaning to big data. They have increasingly gained traction in public and private sectors as 'sense makers' in the age of big data flows. Thus, AI is used to make sense of large amounts of data, predict patterns, analyse risks and act on that knowledge in healthcare, manufacturing, public administration, social networking, finance and most other areas in society. A survey of AI uptake in Europe found that four in ten enterprises (42%) have adopted at least one AI program, with a quarter of them having already adopted at least two.[18] Business and technology companies have generally started rebranding their big data efforts as 'AI'[19] and, in the policy-making field, AI has gained strategic importance worldwide. In public and private sectors, decision-making processes are progressively informed by and even replaced by big data AI systems. Risk assessment systems look for patterns in the backgrounds of defendants to inform judges about who would be most likely to commit a crime in the future. Personalisation and recommendation systems are creating profiles based on our personal data to decide what we see and read, and whom we engage with online. Triage systems analyse the medical records and the demographic information of patients to decide who gets a new kidney. In their current form, AI systems amount to very little without data and most of them need data to be available, accessible, collected and stored. As the Data Governance Working Group (WG) of the Global Partnership of AI (GPAI) highlights in a report on AI data:

> *...data availability (whether data exists) and accessibility (whether data is accessible) are the main driver behind development of products that use AI technologies.*[20]

Businesses, economies and policies are changing alongside the adoption of new AI and big data socio-technical infrastructures, and with them, so are the moral decisions and choices which are increasingly intertwined with the complex data processing of AI systems. Accordingly, interests in the fuel of AI—data—as a resource to acquire, protect and share come together in efforts to direct the development of AI in society.[21]

Data pollution as a term speaks into a new green movement for data sustainability. The global environmental movement originally took form as a response to the tangible environmental impact of industrial development and urbanization, such as the introduction of harmful pollutants in our natural environments, habitat reduction/changes, the extinction of different species, and damage to the land, water, and forests. Tackling this sort of environmental impact became a driver for entire new legal frameworks and policies, and national and international environmental laws. It transformed entire sectors, like the car industry, and drove forward the development of new fields and sciences, like ESTs, 'green tech'. Today, we are experiencing a similar process when articulating our societal response to what computer security and privacy technologist Bruce Schneier described in 2006 as the core environmental problem of the age of big age:

> *…this tidal wave of data is the pollution problem of the information age. All information processes produce it. If we ignore the problem, it will stay around forever. And the only way to successfully deal with it is to pass laws regulating its generation, use and eventual disposal.*[22]

We have had policy and public debate on the privacy and social implications of big data since the early 2000s, and we are now having more serious conversations about the carbon footprint of data storage and processing. Moreover, society is starting to have a conversation about the most powerful actors in this field, such as regions, governments, intergovernmental organisations and tech giants. Nevertheless, there is still very little awareness about data pollution as an 'environmental problem' and its disturbance of entire ecosystems. What is needed is a new green movement for data pollution and a better understanding of the power dynamics that shape the field across different data pollution issues. In that regard, many of the concepts of the global environmental movement and 'sustainable development' discourse in policy and business can be reappropriated to help map and identify data pollution and power.

Data Pollution

Data pollution is the interrelated adverse impact that the generation, storing, handling and processing of digital data has on our natural environment, social environment and personal environment. It is the unsustainable handling, distribution and generation of data resources. Data pollution due diligence means managing—in organisational, policy and *design practice—the adverse effects and risks of data exhaust on natural, social and personal ecosystems.*

Since the mid 1990s, we have seen a transformation of our societies enabled by computer technologies and directed by a conversion of just about everything into various data formats (*datafication*).[23] Big data is a movement driven by a particular vision about of the role of digitalised data in society.[24] For many years, industries, governments and scientists have perceived big data as an end in itself, with the promise of unlimited future uses; an endless resource that will never run out and therefore is distinct from other natural resources, which can be exhausted (like oil or water).[25] Nevertheless, big data is increasingly also understood as a societal force for change that, like industrialisation, not only has brought about growth, but also has negative consequences, including the impact that we see on our natural environment in the form of climate change.

Two traditional usages of the term data pollution can thus be combined:

Firstly, data pollution can be understood as the adverse impact on *personal and social environments*, for instance on individual rights, such as data protection or the right to private life, and on democratic institutions and balances of power. Secondly, data pollution can be understood as the material adverse effects on our *natural environment*, e.g., the carbon footprint of big data.[26]

1. **Impact on social and personal environments**

Originally, the term data pollution was used to refer to the invisible data asymmetries of power of a growing big data economy and the datafication of individual lives and societies. As such, data pollution came to represent the concrete adverse consequences of big data for personal and social environments. Thus, with this term, Schneier emphasised the very real and material effects of the massive collection and processing of big data by companies and governments alike on people's right to privacy.[27] Following this, 'data pollution' has been expanded in the definition of a more holistic governance approach to the adverse effects of the big data economy, recognizing that not only are personal environments at stake, but also social environments. As we stated in 2016 in *Data Ethics. The New Competitive Advantage* when defining and carving out a role for the term 'data ethics' in policy and public debates on big data:[28]

Individual privacy is not the only societal value under pressure in the current data-saturated infrastructure. The effects of data practices without ethics can be manifold – unjust treatment, discrimination and unequal opportunities. But privacy is at its core. It's the needle on the gauge of society's power balance.[29]

Since then, Ben-Shahar has introduced data pollution in the legal field as a way to *rethink the harms of the data economy* to manage the *negative externalities* of big data with an *environmental law for data protection* recognizing that harmful data exhaust is not only disrupting the privacy and data protection rights of individuals, but also has an adverse impact on an entire digital ecosystem of social institutions and public interest:[30]

The concept of data pollution invites us to expand the focus and examine the ways that the collection of personal data affects institutions and groups of people—beyond those whose data are taken, and apart from the harm to their privacy.[31]

2. **Impact on the natural environment**

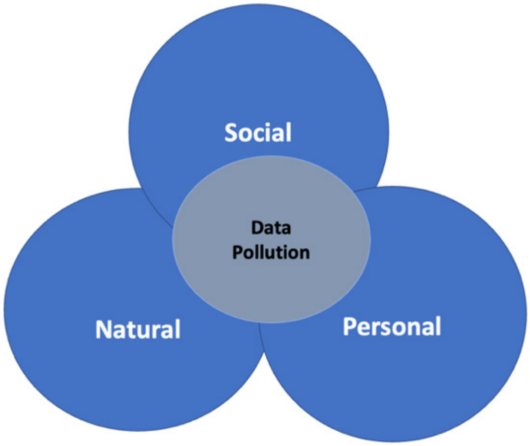
The other strand of usages of the term data pollution addresses the more traditional environmental impact of big data on our natural environment. This is what Lucivero and Samuel, along with an interdisciplinary group of scholars, refer to as *data driven unsustainability.*[32] The impact on the natural environment caused by the data pollution of digital technologies is due to its complexity, which, however difficult it may be to get a full picture of, is undeniable. The French thinktank advocating a shift to a post-carbon economy, the Shift Project, estimates that the share of global greenhouse gas emissions produced by data had increased from 2.5% in 2013 to 3.7% in 2019.[33] In that regard, data centres account for 1% (and steadily growing) of total global electricity demand. The majority of this growth is attributed to cloud computing by the largest big data companies such as Amazon, Google and Microsoft.[34] The impact of data-intensive technologies, such as AI, is also significant. For example, a famous study by Strubell et al. found that training (including tuning and experimentation) a large AI model for natural language processing, such as machine translation, uses seven times more carbon than an average human in one year.[35] Importantly, the environmental pollution of data-driven digital technologies, such as AI, is not only an issue of data, but also ICT disposal and consequences more difficult to discern (such as consumers' energy consumption when making use of digital services).[36]

For the purposes of this white paper, these two usages of the term data pollution are combined with the aim to identify data pollution in a common ecosystem of power and, accordingly, to consider actions with a more holistic governance approach to the pollution problem caused by the age of big data. The UN 2030 Agenda for Sustainable

Development, which was adopted by all United Nations Member States in 2015, established sustainability as an interrelated issue to be tackled across various fields of action. Accordingly, the 17 Sustainable Development Goals (SDGs) of the agenda address the balance of three dimensions of sustainable development—economic, social and environmental—with strategies to grapple with climate change, improve health and education, reduce inequality, and stimulate economic growth. [37] In the white paper, data pollution is addressed similarly as not only one type of environmental impact, but rather as the interrelated adverse effects on delicate balances in our natural, social and personal ecosystems and environments.[38]

As described, the term data pollution is currently used to emphasise the very real and material adverse environmental impact of big data on these environments. As follows, the goal of a new 'green movement' for big data is 'data sustainability', which cuts across the SDGs with sustainability considerations connected to the various environmental changes caused by the volume and diversity of big data, ranging from its effects on the natural landscape to our decisions and democracy [39] (see also the eight data pollution domains).

The assumption is that data pollution does not take one easily identifiable form. It impacts entire eco systems of 'material' and 'non-material' environments altogether. Thus, no matter the definition being referred to, the impact of data pollution on our social, personal or natural environments is as 'real' and 'material' as the pollutants of the Industrial Age and must be managed as such. This also means that we cannot tackle one adverse effect without also tackling others. A company, for example, cannot claim to have 'sustainable data practices' by reducing its carbon footprint alone, while at the same time failing to manage the risks that big data handling, storage and processing poses to our personal and social environments. True data sustainability means taking into account the entire complex of an interrelated eco system impacted by the datafication of our societies



The Holistic Approach

A holistic approach to data pollution encompasses the complexity of the socio-technical powers of our 21st-century big data society with micro, meso and macro level analyses. The presumption is that data pollution is embedded in complex, very real and material interrelated architectures of powers. It is at once a design, cultural and social, organisational and geo-political issue. The presumption is that our identification of data pollution and societal responses to it are simultaneously enabled and inhibited by structural power dynamics.

Alongside the introduction of big data and AI in society, we are experiencing a concrete transformation of the objective qualities of a material and non-material (social and personal) spatial environment. That is, electronic global and local digital realities have real qualities that form the architecture of our realities. They represent existing forces of power while also transforming them. In this way, we may also describe our present digitalised global space as an expression of the expansion 19th-century capitalism and industrialisation. In other words: we are experiencing the compression of time and space created mainly for the operations of capital.[40] Ours is a global society characterised by forms of power, materialised in the virtual architecture and flows of global and digitalised networks.[41] That is, societal power is no longer fixed in places, like the nation state, but is distributed in the very information architecture of socio-technical systems.

We may thus understand data pollution and power in the context of larger socio-technical transformations in global societies, but at the same time knots of power are unravelled in the context of design and engineering practices that shape spatial digital infrastructures. In this way, we might, for example, detect a link between a lack of reflection by AI practitioners regarding the impact of their design choices on the personal, social or natural environment and data pollution as a global environmental problem. The complexity of issues that move beyond traditional boundaries of practice equally complicate ethical reflection at a local/micro level. Data pollution is indeed a complex environmental problem in need of more holistic solutions.

We can here use a *multi-level analysis*[42] that encompasses both micro, meso and macro perspectives on data pollution to grasp the complexity of their socio-technical environments and power dynamics. The aim is to move beyond a reductive analysis of complex socio-technical developments focusing on either the micro dynamics of, for example, designers and engineers of a technology or, on the other hand, only focusing on larger macro-economic or ideological patterns. A narrow focus on data pollution in the micro contexts of design will not comprehend the wider social conditions and power dynamics for change, while a correspondingly narrow analysis of macro power dynamics and social change will reduce individual nuances and factors by making sense of them only in terms of these larger societal dynamics. A multi-level analysis, on the other hand, allows for the exploration of a more complex environment.[43]

In terms of an analysis of data pollution, this also means approaching the issue as a movement between different *scales of time* [44] to detect larger patterns of technological innovation and consolidation on a historical scale, while simultaneously understanding their specific life cycles.[45] In this way, we can at the same time understand their political, organisational and cultural contexts.

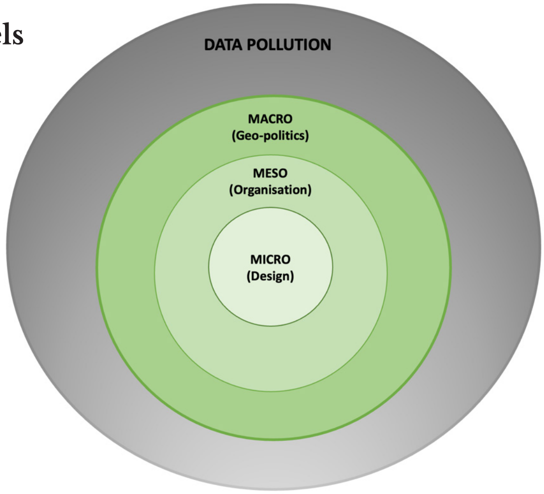
Thus, these three levels of analysis (micro, meso and macro) are central to the delineation of the power dynamics that give shape to data pollution and our response to it:

On the **micro level**, powers and interests in data can be identified in the very design of an AI system. Here, we want to understand data pollution of the very data design of AI. Where is the data pollution in the data ecosystem of an AI program? Which interests are embedded in the data design process? How are data design choices made? Are there alternative, more sustainable data design options available? What are the barriers and enablers on a micro design level for tackling data pollution and achieving sustainable AI data?

On the **meso level**, institutions, companies, governments and intergovernmental organisations will be negotiating the interests, values and cultural frameworks of their practices in contexts of standards and laws. How are laws and standards implemented within an organisation? Which interests are emphasised in the implementation of institutional, standardised frameworks? What are the barriers and enablers on an institutional, organisational and governmental meso level for tackling data pollution and achieving sustainable AI data?

Sociotechnical change happens on a **macro level** in terms of interest negotiations in what constitute *the technological momentum* that a larger socio-technical system needs to evolve and consolidate.[46] Our increasing awareness of the data pollution of AI is integral to a current critical moment in which different societal interests are being negotiated on a macro level in society and expressed in cultures, norms and histories on macro scales of time. This is where we see the conflicts between different systems, political and business 'narratives' of change and innovation, and it is where critical problems are exposed, solutions are negotiated, and different interests are finally gathered around solutions to direct the evolution of technological developments. In this regard, we want to understand the power dynamics of the geo-political battle between different approaches to data and AI. How do the political and social discourses, legal twists and cultural tensions shape how we tackle data pollution of AI on a macro level and scale? What are the barriers and enablers on a historical and geo-political level for tackling data pollution and achieving sustainable AI data?

The Three Data Pollution Levels of Analysis



The Human-Centric Approach

The human-centric approach to AI concerns the ethical responsibility of humans and the preservation of human dynamic qualities and empowerment in socio-technical AI infrastructures. The approach gained momentum in the late 2010s in global policy discourses on AI as a human rights and risk-based approach of the EU's Artificial Intelligence strategies and policy instruments and the ethics recommendations and principles of intergovernmental organisations, such as the OECD and UNESCO.[47]

The 'people-centred' approach to ICT governance was the foundation of early international multistakeholder initiatives on the regulation of the global information society. As stated in the Declaration of Principles published in correlation with the World Summit on the Information Society that was supported by 50 heads of state/governments and vice-presidents, 82 ministers, and 26 vice-ministers and heads of delegation as well as high-level representatives from international organisations, the private sector, and civil society:

We, the representatives of the peoples of the world, assembled in Geneva from 10-12 December 2003 for the first phase of the World Summit on the Information Society, declare our common desire and commitment to build a people-centred, inclusive and development-oriented Information Society, where everyone can create, access, utilize and share information and knowledge, enabling individuals, communities and peoples to achieve their full potential in promoting their sustainable development and improving their quality of life, premised on the purposes and principles of the Charter of the United Nations and respecting fully and upholding the Universal Declaration of Human Rights.[48]

A similar human rights-based approach later gained momentum more specifically in the late 2010s in global policy discourses on AI as the 'human-centric' approach to AI. It was first emphasised in the EU's Artificial Intelligence strategies and policy instruments published in 2018.[49] The European Commission's Communication on AI published in the beginning of that same year, for example, described an anticipatory approach that invests in people as *a cornerstone of a human-centric, inclusive approach to AI* and also refers to *putting the human at the centre*, based on the Responsible Research and Innovation (RRI) principle that guides research funded within the EU's Framework Programmes.[50] The Coordinated Plan on AI published in December 2018 outlined the unique position and global ambition of the EU: *to become the world-leading region for developing and deploying cutting-edge, ethical and secure AI, promoting a human-centric approach in the global context*.

The human-centric approach also became the guiding framework for the EU High-Level Expert Group on AI ethics guidelines published in 2019. This was importantly recognised as a 'fundamental rights-based' approach stemming from the EU Charter of Fundamental Rights. The same year, AI principles that emphasised *human-centred values and fairness* in particular were adopted by OECD member countries. In 2021, the Recommendation on the Ethics of Artificial Intelligence was adopted by UNESCO's General Conference guided by the more traditional human rights values-based framework to *respect, protect and promote human rights and fundamental freedoms and human dignity.*[51]

Regardless of the different institutional settings, global positions and historical paths towards a human-centric approach to AI, these 'ethical governance'[52] initiatives have a common objective to 'do good' while also managing the associated risks and ethical implications of AI. However, what is also important to note is that, aside from an emphasis on the special role and status of humans, no shared conceptualisation of how to achieve that goal exists.

Policy debates on the role of people, ethics and values in technological development have been ongoing since the 1990s as a response to accelerated progress in science—biology and medicine in particular[53] The Council of Europe's Oviedo Convention (the Bioethics Convention), for instance, emphasises the interest of the human being:

Primacy of the human being. The interests and welfare of the human being shall prevail over the sole interest of society or science.[54]

One contemporary critique of the human-centric governance approach to AI evidently concerns presumed anthropocentricism, i.e., that this approach is primarily concerned with individual people and the human species as such.[55] Yet, there is also a different way to understand this approach. Rather than 'human-centrism' we may instead refer to a 'human approach'.[56] A 'human approach' is one that is concerned with the role of the human as an ethical being with a corresponding ethical responsibility for not only ourselves but for life and being in general. It thus follows that people's dynamic qualities are prioritised when developing socio-technical infrastructures of human empowerment.[57] In design and engineering contexts, the term 'human-centred design' (HCD) has existed for many decades, encompassing an approach to ICT system development that focuses on user needs, knowledge, well-being and other factors, including adverse effects and risks to humans. While a human(-centric) governance approach[58] does indeed foster HCD in relation to AI systems focused on individual human beings and their needs, the ultimate objective goes beyond the individual human being only when considering first and foremost the role of people and human governance in ecosystems—e.g. the role of the empowered citizen in the ecosystem of a democracy, the role of an individual consumer in the ecosystem of consumption and the natural environment when making well-informed environmentally friendly choices, or the role of a group of democratically elected policymakers that create policies that support environmentally sound science and technology development. This sort of 'human(-centric) approach' is thus *not just about humans—it* is *human.*[59]

Importantly, the human (-centric) approach also constitutes a foundational critique of more traditional utilitarian AI development frameworks that do not encompass a humanist, holistic reflection on the role of people and their 'artefacts' in delicately balanced eco-systems. The impact of human science and technology on the natural environment in the form of climate change is, for instance, evidence of the foundational problems of the utilitarian approach. As a species, throughout history humans have proven to be both a creative and destructive force on Earth, and while climate change is a product of the more destructive kind of human activity, humans also comprise a creative productive force that can readjust and craft changes through man-made tools (technology). AI is taking centre stage as a technology that can mitigate environmental challenges. It can be used to understand and lessen climate change with, for example, predictions, pattern recognition, optimisation of resources etc. However, like most human products, it also carries with it risks and harm that may contribute to climate change. In this context, we can also think of the human-centric approach that is expressed in recent AI ethical governance initiatives as faith in humanity, as recognition that humans have the power to reflect on their impact on and disturbance of social ecosystems and those of planet Earth, and as an appreciation of the human capacity to be critical, to readjust and to craft alternative realities and steer sustainable developments. We see this expressed in policies on sustainable development and the green transition which recognise that digital technologies (AI in particular) are enablers of sustainable development goals in many different sectors, but simultaneously that we need to also create sustainable alternative technologies and methodologies and to reduce the energy consumed by AI.[60]

This is a critical moment in which human governance, so far driven by tunnel-vision interests, can be replaced by a more holistic approach to the environment that embraces the complexity of such a sensitive ecosystem.

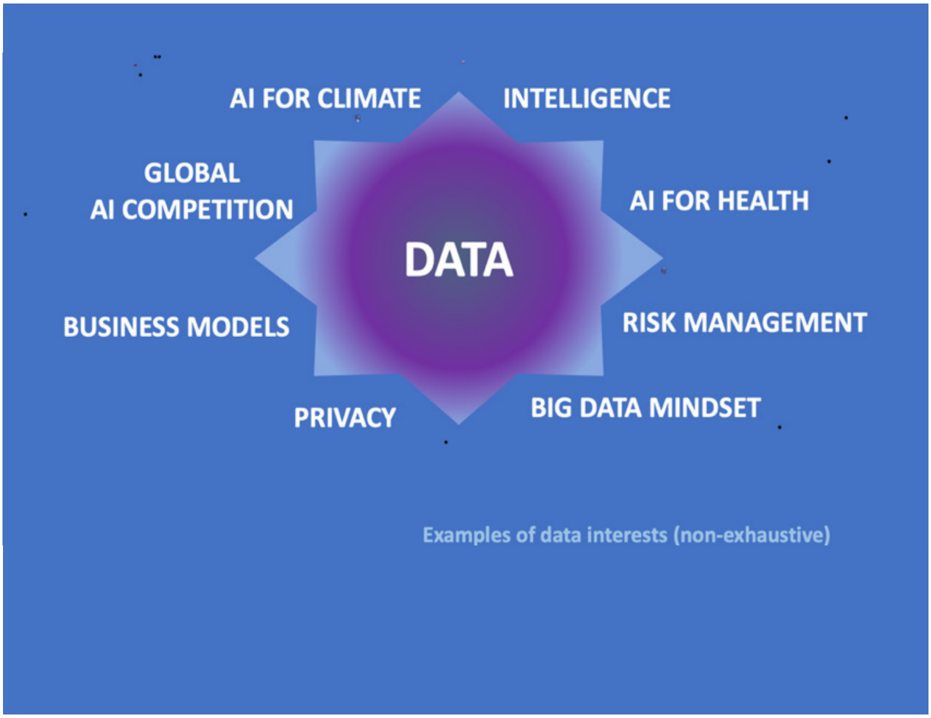
Data Ethics of Power

Values and interests are core components of sociotechnical change. When identifying the data pollution of AI and exploring constructive actions to tackle its environmental impact, we need to consider the interests in data invested in the design of AI, and also AI and data governance. *Data Ethics of Power*[61] is an applied ethics approach concerned with making the power dynamics of the big data society and the conditions of their negotiation visible in order to point to design, business, policy, and social and cultural processes that support a human(-centric) distribution of power.

Data Interests

A 'data interest' constitutes a specific need, value or goal centred on data as a resource.[62] *This can be political, commercial, or scientific interests in data or an individual's interest in protecting or making use of their personal data. Data interests can be found in data design and in data governance activities.*[63]

To develop actions that tackle AI data pollution and support sustainable AI and data, we first need to explore how interests are embedded in the knowledge and values-based worldviews and frameworks that shape the practices, development and adoption of big data and AI systems. Data interests can be explicitly examined during different design and deployment phases of AI. They can be examined as negotiations between different interests in digital data. They represent micro individual stakeholder objectives, values and needs (for instance, the interest of developers, users, institutions or businesses in data) or they may even represent macro cultural sentiments or social and legal requirements. Thus, examining them with different levels of analytical interpretation (micro, meso, and macro) is important if we are to understand their interrelated power structures.



2.

THE GEO-POLITICS OF DATA POLLUTION

THROUGHOUT HISTORY AWARENESS OF the role of data and AI in society and the economy has emerged in varied sectors, ranging from scientific fields and discourses of the 1950s (e.g., early mathematics and computer science) to the business culture and mindset of the big data hype of the 1990s, to then take form in the global AI policy discourses of the late 2010s. In particular, the sustainability and ethical implications of AI and data are now integral to the main governmental and intergovernmental agendas and policy documents of global power actors. To politically govern the macro challenges of data pollution, a holistic approach and coordinated global approach among key power actors is needed. Nevertheless, the role of big data storage and AI processing, and the impact on the personal, social and natural environment are currently mostly addressed separately, and managed in distinct policy fields.[64]

In public discourse, geopolitics surrounding AI have been dubbed the 'global AI race'. It stands between world regions and can be considered the result of the scientific paradigms, histories and design cultures of the evolution of computer and information technologies and big data environments. Imagined and developed within the confines of the science lab decades ago, AI systems have today evolved and moved outside the lab into private and public sectors, extending key decision-making processes with new critical infrastructures infused with AI prediction and analysis. When mathematics professor John McCarthy coined the term 'artificial intelligence' at the Dartmouth Summer Research Project seminar in 1956, computer scientists and mathematicians working in the field were primarily focused on the automation of computation processes. However, McCarthy wanted to explore how computation could move beyond processing information only, to think and learn from information like humans.[65] In the following years, the field was shaped by efforts to develop expert systems that were based on programmed rules and human expertise. In the 1990s and 2000s, the advancement of digital technologies—with the conversion of all types of information from photos to audio recordings into a set of numbers that could be processed by computers—enabled the collection of huge amounts of data.[66] This digitalised big data environment became the foundation of what are today called 'machine learning' systems, the most practical application of AI in the early 21st century. With machine learning, an AI system no longer needs a human expert as the basis of knowledge. Instead, the system learns and evolves with data, thereby gaining autonomy or semi-autonomy.

The competition among regional players for global leadership in the field of AI research, development and innovation has always been characterised by negotiations regarding the power, values and interests that have materialised in the invention and consolidation of our socio-technical environments. Those interests cover various issues, such as AI data resources, capital investment, AI technical innovation, practical and commercially viable research and education, and even the 'ethics' of data and AI. Thus, not only AI research and innovation, but also risk mitigation and governance have become forms of *cultural positioning* and competitive advantages in the momentum of 21st-century global AI.[67] Essentially, it is a competition between different powers that still does not yet represent a united trajectory for humankind or the protection of the planet.[68]

The current geo-political negotiations and regional positioning on AI, especially in terms of ethical awareness and risk-based approaches, may appear novel in a public discourse which until only recently was characterised by the technology worship and thrill of the 1990s and early 2000s. However, geo-political concerns with the adverse effects and disturbance of the natural environment and eco-systems caused by man-made technological progress have always been at the core of the global sustainable development agenda. The Human Environment Conference that took place in Stockholm, Sweden in 1972 was the first global conference to recognise the impact of human science and technology on the environment, stating the urgency to collaborate and act globally:[69]

In the long and tortuous evolution of the human race on this planet, a stage has been reached when, through the rapid acceleration of science and technology, man has acquired the power to transform his environment in countless ways and on an unprecedented scale.[70]

Delegations from 114 governments attended the conference, and the pre-conference activities in Stockholm brought together thousands of unofficial observers from all over the world. This was also where the term 'Environmentally Sound Technologies' (ESTs) was coined to represent technologies (or rather entire technological systems) that can help reduce environmental pollution while at the same time being sustainable by design and during their implementation and adoption.

In 1992, the Agenda 21 action plan was created at the United Nations Conference on Environment and Development (UNCED) (also known as the Earth Summit) held in Rio de Janeiro, Brazil, which brought together multiple stakeholders from 179 countries to discuss the impact of human socio-economic activities on the environment. The agenda called for governments and other powerful stakeholders to implement a range of strategies to achieve sustainable development in the 21st century (among other topics), restating the need for the development and transfer of ESTs.

Environmentally sound technologies protect the environment, are less polluting, use all resources in a more sustainable manner, recycle more of their wastes and products, and handle residual wastes in a more acceptable manner than the technologies for which they were substitutes.[71]

In 2015, the UN adopted the 17 Sustainable Development Goals (SDGs), equally emphasising not only the need for ESTs to help reach those goals, but also restating that this required the adoption of alternative, environmentally sound development strategies and technologies.[72]

The 'trustworthy' and 'human-centric' AI policy agenda (described previously as the human-centric governance approach to AI) has evolved alongside that of a global sustainable development agenda. The recent political narrative on AI and sustainability in particular is thus not an arbitrary emphasis. Intertwined with the awareness of and intention to tackle the social and ethical implications of AI, there is also a broader global policy agenda regarding the environmental impact of science and technology which has evolved over decades. However, only lately have political objectives on the role of AI in sustainable development turned into a more globally shared political goal. Along with other changes, this happened due to a merger between the environmental global policy agenda and the information society/internet governance agenda relating to the human rights implications of ICTs and the ethics of AI.

As described previously, governments and intergovernmental organisations around the world have, in recent years, proposed and presented AI ethics principles and recommendations as well as general political strategies that, while aiming to ensure good market conditions, innovation and scientific development in the field of AI, have set in motion governance activities that address the social and ethical impacts of AI. Looking at them in detail, they include several early statements and intentions on the environmental impact of AI.

Europe in particular is leading the development of policies and regulation on trustworthy and sustainable AI. The European Green Deal (2019) mentions several environmental concerns in regards to AI and stresses that 'sustainability' must be a core point of departure for the development of not only AI technologies, but a digitised society in general. For example, it states:

> *[...] Europe needs a digital sector that puts sustainability at its heart. The Commission will also consider measures to improve the energy efficiency and circular economy performance of the sector itself, from broadband networks to data centres and ICT devices. The Commission will assess the need for more transparency on the environmental impact of electronic communication services, more stringent measures when deploying new networks and the benefits of supporting 'take-back' schemes to incentivise people to return their unwanted devices such as mobile phones, tablets and chargers.*[73]

Furthermore, the EU's Coordinated plan on AI (2018) stated:

[...] AI uptake requires access to dedicated low-power AI processors that provide the necessary processing power and are more efficient, by several orders of magnitude, than general-purpose processors.[74]

Moreover, it mentions the intention to support research in 'greener AI', simultaneously addressing the energy consumption of AI and potentially including 'environmental score' criteria in the public procurement of AI.[75] This was reviewed in 2021 with the *Communication on Fostering a European approach to artificial intelligence*[76] and a revised coordinated plan[77] restating the role of AI in reaching European Green Deal objectives, and the intention to build strategic leadership in sectors including climate change and the environment, as well as a focus on building a Green Deal data space and the incorporation of environmental questions in international coordination and cooperation on AI. Importantly, this also includes the intention to explore the definition of key performance indicators to identify and measure the negative and positive environmental impact of AI, building on the European Commission's work on resource and energy-efficient and sustainable infrastructure for data storage and processing.

Notably, following the first launch of the EU's Coordinated AI plan in 2018, the EU High-Level Group on AI (HLEG) was established in 2018, composed of 52 selected members consisting of individual experts and representatives from different stakeholder groups. Tasked with the development of ethical guidelines and policy and investment recommendations for the EU, the group developed seven key requirements that AI should meet in order to be deemed 'trustworthy', with one in specific emphasising 'social and environmental well-being':

AI systems should benefit all human beings, including future generations.

It must hence be ensured that they are sustainable and environmentally friendly. Moreover, they should take into account the environment, including other living beings, and their social and societal impact should be carefully considered.[78]

The establishment and negotiation of the requirements of the HLEG's ethics guidelines illustrate this dawning awareness of the environmental impact of AI on the social and natural environment in the region's policy-framed ethics work. At the time of the establishment of the HLEG on AI, the European Commission had around 700 active expert groups that were tasked with drafting opinions or reports advising it on particular subjects. The work of these high-level expert groups is not binding, and the EC is independent in the way it is used.[79] Nevertheless, when the HLEG on AI presented its ethics guidelines to the European Commission in March 2019, a communication was published shortly after: *Building Trust in Human-Centric AI*. In it, the HLEG stated its support for the seven key requirements of the guidelines and encouraged all stakeholders to implement them when developing, deploying or using an AI system. At the end of 2019, the then newly elected President of the European Commission, Ursula von der Leyen, stated: *In my first 100 days in office, I will put forward legislation for a coordinated European approach on the human and ethical implications of Artificial Intelligence*.[80]

Notwithstanding, while most of the HLEG's recommendations were reflected in the European Commission's AI Act proposal that followed in 2021 in the form of mandatory requirements for high-risk AI, *social and environmental well-being* was not. In another part of the world, the US Department of Commerce's National Institute of Standards and Technology (NIST) drafted an AI Risk Management Framework which was presented in March 2022: similarly, it did not include a reference to the environmental impact and risks of AI.

While this does not necessarily reflect the lack of political will to act on the environmental impact of AI, what is missing is the coordination of policy efforts within and across regions, in order to reach shared goals regarding sustainability in general and in relation to AI.

The sustainable development agenda (which considers both positive and negative environmental impact of green technologies) only recently moved into the geo-political agenda on AI. Though gradual, we are increasingly seeing the recognition that technology such as AI can help us reach sustainable development goals, while also acknowledging the fact that, in and of itself, AI can have adverse environmental consequences (as a man-made component of the environment) and accordingly the urgent need to address the sustainable development and implementation of AI. For example, once the EU AI Act proposal reached the EU parliament negotiation stage in 2022, environmental considerations were included. In addition, several other policy instruments in Europe with a geo-political impact and/or attention reflect an awareness of and political willingness to act on not only the environmental fallout of AI, but on data pollution in particular. For instance, the EU Data Strategy of 2020 describes the legal components and governance approach to create a common European data space and a single market where data can be shared for thematic areas, such as the European Green Deal. Furthermore, the 2021 ‘Digital Decade’ strategy that constitutes the European Commission’s vision for the development of the European digital economy and the transformation of European businesses by 2030 emphasises the need to address the sustainability of data.[81]

More specifically, in 2021 an increasing number of initiatives and statements were published worldwide with the aim of ensuring global collaboration in areas such as the development of sustainable AI and with an emphasis on the environmental impact of AI and data. The US and EU Trade and Technology Council (TTC) came out that year with an inaugural joint statement with several items on AI and the creation of a working group on the climate and clean tech that is meant to identify opportunities, measures and incentives to support technology development, transatlantic trade and investment in climate-neutral technologies, products and services, and, importantly, to include collaboration with *third countries* (as they are referred to in the TTC Inaugural Joint Statement) to jointly explore methodologies and tools.[82] In addition, in September 2021, the European Commission's Service for Foreign Policy Instruments (FPI) and the Directorate General for Communications Networks, Content and Technology (DG CONNECT), in collaboration with the European External Action Services (EEAS), officially launched its International Outreach for Human-Centric Artificial Intelligence (InTouchAI.eu)[83] initiative to help *promote the EU's vision on sustainable and trustworthy AI*, a large foreign policy instrument project engaging with international partners on regulatory and ethical issues of AI at a global level.[84] Moreover, in December 2021, the European Commission and the High Representative for Foreign Affairs and Security Policy launched a new European Strategy (Global Gateway) to *boost smart, clean and secure links in digital, energy and transport and strengthen health, education and research systems across the world*.[85]

All of this happened a couple of years into the Covid-19 pandemic, which has forced global collaboration on global challenges in many policy spheres (including the digital sphere, with Covid-19 'passes' and contact tracing apps). At the same time, a number of AI documents were produced with geo-political significance illustrating a crucial awareness among global stakeholders of the environmental impact of data and AI. Noticeably and with forceful global recognition, in November 2021 UNESCO member states adopted the Recommendation on the Ethics of Artificial Intelligence which, among other things, states that actors involved in the life cycle of AI systems:

[...] should reduce the environmental impact of AI systems, including but not limited to its carbon footprint, to ensure the minimization of climate change and environmental risk factors, and prevent the unsustainable exploitation, use and transformation of natural resources contributing to the deterioration of the environment and the degradation of ecosystems. [86]

Furthermore, that same month, the Responsible AI group of the Global Partnership on Artificial Intelligence (GPAI)—a multi-stakeholder initiative set up by 15 countries in 2020 that expanded to 25 country members in 2021—published *Climate Change & AI: Recommendations for Government*. This influential report includes key recommendations on reducing the negative impact of AI on the climate by, for example, incorporating climate impact considerations into AI regulation strategies, funding mechanisms, and procurement programmes.[87] Additionally, in late 2021 the voice of companies and enterprises around the globe, the World Economic Forum, published *The AI Governance Journey: Development and Opportunities*, an insight report acknowledging AI as an emitter of carbon and thus the need to address the issue through global collaboration:[88]

As knowledgeable as we have become in tackling some areas, a considerable amount of thought and work remains on other downstream effects of AI on the planet. Though certainly championed for its potential to help tackle global issues such as climate change, the infrastructure around AI systems has also come under scrutiny for its carbon output.

It should be noted that the conceptualisation and implementation of 'data sharing' infrastructures for Earth observation and climate data, among other things, has received attention as part of the sustainable development agenda. It is an essential foundation for global coordination on the mitigation of climate change in particular, with several international initiatives aiming at the creation of open data spaces with global reach. One example is the Destination Earth (DestinE) project: set up as part of the European Commission's Green Deal and Digital Strategy, its aim is to develop, on a global scale, a digital model of the Earth to monitor and predict the interaction between natural phenomena and human activities.[89] Global initiatives and statements on the sustainable use of data in particular have been set up also. For example, in October 2021, at the UN's World Data Forum, leading statisticians working in the international statistical system called for a Global Data Convention to safeguard sustainable development.[90]

In conclusion, it has become increasingly evident that the impact of AI data on the natural, social and personal environment deserves a place in the geopolitics of the agenda on sustainable development. Because of its adverse environmental consequences, a global digital environment simply cannot evolve without a globally coordinated political agenda that aims to ensure sustainable design, innovation, business and implementation. It is also the reason why avid attention must be paid to the political and social discourses and interest negotiations that are today shaping the geopolitical response to the data pollution of AI. As of now, awareness of the adverse effects of big data storage and processing among dominant geopolitical powers is evolving, and diverse political responses are emerging in different regions and within different frameworks and fields of governance. However, a more holistic coordinated geo-political response is still nascent. For instance, most environmental data sharing initiatives are not asking if or how the energy costs of AI and, in particular the data, required for global AI systems for climate change should be weighed against the benefits of their deployment.

What we need to understand now is how political, social and design cultures on data and AI evolve in the context of these different geo-political agendas and the negotiation that takes place between the various societal interests invested there. On this matter, we need a clearer view of the macro powers and interests that are competing in this field, i.e., the power dynamics of the geo-political battle between different approaches to data and AI. Thus, what also needs further exploration is the level of political awareness of data pollution, and how interests in AI and data are negotiated and finally gathered around solutions that may or may not support a sustainable AI global narrative of change.

The still-dominant narrative of the early aspirations of AI researchers to achieve human-level *intelligence* for computers and the big data thrills of the late 20th and early 21st centuries do not fully encompass the environmental problems of data and AI. This is why we need a new narrative for AI data, one that would help reveal the challenges we are unable to see today. Adding data pollution to the geopolitical sustainable development agenda, for instance, opens up yet another global power problem which rests in the very constitution of not only multistakeholder, but also multi-community and regional participation in the creation of the emerging sustainable AI agenda. That is: those who are currently defining problems, identifying solutions and determining the speed of their implementation, are the ones who already have an AI infrastructural advantage.[91] In today's information-driven and networked global society, power is integrated in very real and material digital data architectures and, as is increasingly highlighted in public debate, these digital architectures most often sustain the already-powerful while putting others at a disadvantage. The asymmetries reproduced in the architecture of the big data society and the political narratives shaping it are replicated in very different experiences of data pollution and also in the exclusion from participation in global agenda-setting discourses on trustworthy AI and sustainability. For example, while citizens of developing countries are experiencing the adverse effects of data pollution on their natural environments, rarely do they have a say in the global sustainable development debate on AI.

Power asymmetries may be traced back to the formation of AI as an innovation and marketplace dominated by a few technology giants. Firstly, we may refer here to a form of 'digital colonialism' (which will be further explored in the next chapter in the context of 'global opportunities') powered by dependency on these few technology giants, e.g., the dominant cloud providers on which AI developers depend. A recent report drafted for the Africa Policy Research Institute by Rachel Adams on AI in Africa illustrates the gap between the production and development of AI, which requires the use, availability and extraction of local human and natural resources and the true manifestation of the benefits of AI in that same region.[92] It also outlines the dominance of foreign AI technologies and their incompatibility with local development priorities. This technology dependency is not only further deepening the gap between the 'Global North' and the 'Global South', in fact it also hampers the very act of measuring the carbon emissions of AI and data.[93] Encouragingly, as Adams states in the report, national AI strategies are increasingly being launched with methods and promises regarding the sustainable local development of AI in the Global South. For example, countries across different regions of Africa are developing or about to develop national AI strategies to guide its adoption alongside the development of local AI skills and research, talent attraction, management of the sustainability of AI, the development of open data platforms, etc.

In addition, as associate fellow at ORF's Centre for Security Strategy and Technology Trisha Ray describes it, while technology giants (like Microsoft, Alphabet, Facebook and Amazon) have responded to climate concerns with ‘net zero’ policies and initiatives, they often rely on what she calls *the decades-old inequitable carbon offset system*. At the same time, measuring their carbon emissions is a nearly impossible task due to lack of transparency of the emissions of these companies’ operations, which should include not just their own facilities, but also their broader supply chains.[94]

While the double edge of ESTs has always been part of the global sustainable development agenda, it seems that attention to AI data pollution in particular has been less of a concern in terms of the sustainable AI agenda until only recently. Considering the dominant power dynamics and competing interests represented in the evolution of BDSTIs into AISTIs, we may argue that data pollution is not just a new term for the global sustainable development agenda, but also represents the voice and counter narrative of the minority stakeholders participating (or not) in information society policymaking in general.

3.

CATALOGUE OF DATA POLLUTION DOMAINS

DATA POLLUTION ISSUES TAKE many forms. Neither data pollution practices nor the environmental impact of data pollution can be identified in one area, one sphere of practices or one type of environment. The following is a catalogue of different domains in the natural, social and personal environments where data pollution can have adverse effects. They are explored in terms of the power conditions and contexts that are impacted by data pollution. For issues of clarity, the domains are described individually. However, it is important to note that they are often intrinsically interlinked. Thus, for example, data in the domain of nature will also have an impact on the domain of global opportunities and vice versa. As will be illustrated, this is most often due to interlinked power dynamics in increasingly globalised personal, natural and social environments.

The objective of this catalogue is to help frame data pollution as an environmental problem that extends across several domains. Among other things, the domains arose from discussions at meetings with

1. Nature

To measure and mitigate data pollution in the domain of nature, there is an urgent need to 're-materialise' it.[96] Information and communication technologies (ICTs), data design and AI all constitute not just virtual, but also material infrastructures that pollute the natural environment in very concrete ways. However, this 'materiality' of infrastructure is often neglected in science, policy and business discourse on the limitless data resources of the digital economy and society.[97] *Re-materialising*[98] AI and data means recognising its entire material infrastructure, including the energy it consumes, its hardware and the electronic waste, the mining of precious minerals, its data processing and storage, and the water needed to cool data centres.[99]

Even so, it is an incrementally complex task to measure the extent of AI data pollution and its impact on nature, as this depends on a larger whole made of many individual components, such as the actual power sources used.[100] In fact, when it comes to the impact of, for example, the carbon footprint of AI, what can be most easily measured, as Kaack et al. argue,[101] is most likely not that which has the largest impact, and thus efforts to align machine learning development with climate change strategies, for example, are hampered. They therefore introduce a systematic framework for describing the greenhouse gas emissions of machine learning (ML).

Data pollution in the domain of nature is invisible to AI practitioners, but it can still be addressed as a component of their competencies, education and technological dependencies. Tools for researchers and engineers are being developed to measure the environmental impact of the AI models they develop and train. For instance, the CODECARBON tool is a software package that is integrated into the Python codebase and estimates the amount of carbon dioxide (CO2) produced by the cloud or personal computing resources used to execute a given set of code.[102] It then shows ways to reduce emissions by optimising the code or by hosting cloud infrastructure in geographical regions that use renewable energy sources. Additionally, sustainability management mechanisms can be introduced with 'Sustainability Budgets' implemented in software design, incentivising and rewarding developers and designers for coming up with solutions to reduce the carbon footprint of their programs.[103] Another approach is suggested by the Green Software Foundation, which recommends the creation of alternatives to large AI models that require energy-intensive big data sets and computational infrastructures, and the drafting of standards to measure the carbon footprint of an AI model.[104]

Alternative technologies and methods, and tools and frameworks for AI practitioners to measure, report on and tackle data pollution belong to the micro context of the development of individual AI products and services. Yet, data pollution is not an isolated phenomenon that can be addressed in individual contexts of development and use alone. Data pollution in the domain of nature is the result of a complex set of processes, technology design and, in particular, power dynamics defined by globally distributed technological dependencies and concentrations of power. A global analysis of not only the extent of data pollution is important, but the granularity of the problem is pivotal specially for coordinated responses that are sensitive to the micro contexts of design and use in regions worldwide. However, such an analysis is complicated by the concentration of power in the hands of a few dominant actors in AI design and development. For example, if we want to analyse data centre energy use in regions worldwide, regional data centre statistics can only be obtained from the four main cloud service providers that most AI developers depend on: Amazon Web Services, Google Cloud, IBM Cloud and Microsoft Azure.[105] In other words, data on data pollution in the domain of nature on a global scale is concentrated in the data centres of the very few actors which dominate the technological services used by AI practitioners. This concentration of power adversely impacts the essential granular analysis of data pollution and inhibits coordinated global responses, as many regions with less powerful actors are not represented in statistics on data pollution.

A variety of ethical implications of AI can be mentioned, but one of the ethical issues that is under-researched and under-valued at the moment is environmental consequences, e.g., that there is a link between the 'pollutant effect' of data and AI. When we train algorithms, there are CO2 emissions, electronic waste, mining of precious minerals, etc.

- Aimee van Wynsberghe, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

At the data centre level, there have been calls for more reflection by software engineers and data scientists on the choices that they make and what they run on. Everything is run on big player platforms that make environmental claims that are hard to scrutinise and understand. This is where accountability comes into play as an essential element of governance: issues of transparency and the ability to scrutinise.

- Jenny Brennan, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

Many companies want to use AI to address their sustainability issues in innovative ways, but often the actual impact of such projects is unclear. It is really important to create a means for assessing and evaluating impact and to help industries actually improve things, and prevent projects where in reality nothing changes.

- Lynn H. Kaack, Data Pollution & Power Group, 3rd meeting, 2022

2. Science and Innovation

Data pollution is the outcome of data 'in use' within AI socio-technical systems, but we may also consider 'data exhaust' and 'data spills/waste'—what is also referred to as 'dark data'—which form a majority of the big data stored worldwide. Dark data is data that is not in use but is kept by companies and organisations for compliance reasons or future potential uses. Most of this data is never put to use.[106]

As the accumulation and processing of big data is an environmental problem, the big data interest of AI engineers, industries, policy-makers and data scientists in the domain of AI science and innovation can also be addressed as a fundamental data pollution problem. In a big data economy, the most powerful companies and institutions are guided by a *big data mindset*[107], and practices are dictated by the imagination of big data as an unlimited resource that will not run out like natural resources. Big data holds the promise of endless use and reuse,[108] and the collection and storage of big data becomes an end in and of itself. Success equals the ability to go beyond the limits and borders that lock in data and everything is translated into digital data to *quantify the world*.[109] Thus, locked into the potential of data are problems sought and solved with novel modes of data storage, collection, processing and analysis. New ways of making sense of big data become goals in themselves and, accordingly, AI is perceived as a key to opening up the potential of big data. From this point of view, data pollution initiatives and policies are essentially obstacles, and lobbying efforts on specific legal provisions in the regulation negotiation process would depart from the 'locked-in data potential' problem, also becoming the root of 'check list' and compliance-only cultures in big data and AI science and innovation.

Tackling data pollution in the science and innovation domain requires a counter science and technology-based 'culture of data sustainability', which must be supported in policy, innovation and education. There is a need for environmentally sound development strategies for alternative technologies and, in this regard, we might present and insist on alternative 'realities' of AI design that, for example, do not rely on big data only. Chahal and Toner illustrate how research on ‘small data’ approaches to AI has grown with methods such as transfer learning, data labelling, artificial data generation, Bayesian methods and reinforcement learning.[110] They argue that these small data methods are relevant when enabling AI in areas where there is, by definition, little or no data (for example in forecasting rare natural hazards or in predicting disease for a population with no digital health records), and that pretrained transfer learning models can, for instance, also reduce training time and consequently the computational resources needed to train algorithms.

In healthcare data analysis, we have a tendency to think that the more data the better, or that more data accumulation means more accuracy. Algorithms will be trained with as much data as possible to get that 1% more accuracy in devices and tools, without considering the environmental impact. This is of course not unique to the healthcare sector. It is the same in many other sectors.

- Signe Daugbjerg, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

We talked to academics and stakeholders addressing the issue of what to do with the environmental impact of AI, the digital world and data. We want to understand the values that drive people and how they frame the problem they are trying to address. I think important questions are: Which values are driving this? Who should have responsibility for what? What are the relationships between the different stakeholders? These are descriptive and normative questions about power relationships and data pollution.

- Federica Lucivero, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

3. Democracy

Technologies are highly political and embedded in the dynamics of ruling powers by design and implementation. However, in various ways and with different degrees of force, technologies not only reflect, represent, and reinforce visible politics, established norms and institutional standards of a society, they also transform powers. Thus, just like any technology, AI holds the potential and the risk to either strengthen constitutional democracies or challenge them. How do we understand data pollution in the context of the politics of modern democracies? A democracy is founded on sensitive information balances between citizens and the state, which is stipulated in laws (e.g., human rights laws, charters and conventions), state governance, institutional procedures and frameworks regarding the conduct of elected representatives and public servants. We can refer to this as the information ecosystem of a democracy.

Modern democratic societies need socio-technical infrastructures that reinforce and ensure a democratic ecosystem of information distribution between states and citizens. As a citizen in a democracy, you have the right to access information about state conduct and the right not, for instance, to be subjected to surveillance without reasonable suspicion. Your democratic empowerment as a citizen is based on knowledge about how your personal information is being gathered and processed; it means that you have knowledge about the policies that you are exposed to in order to make informed decisions, for example during elections.

Today, AI is ingrained in society in multiple forms via increasingly complex digital systems that have been developed to contain and make sense of large amounts of data and to act on that knowledge. Socio-technical big data and AI infrastructures (BDSTIs and AISTIs) are also a key component of the politics and the very functioning of modern democracies. Big data and artificial intelligence were key tools in the election campaigns of US Presidents Barack Obama (2012)[111] and Donald Trump (2016).[112] The same can be said of Indian Prime Minister Narendra Modi's election in 2014.[113] Big data and AI do not only form the infrastructure of the elections of political representatives: a democracy is reinforced and implemented by administrations made up of public authorities and public servants. That is, a democracy and its public authorities are mutually supportive as they depend on each other for their everyday operations.[114] In its *Automating Society* annual report, non-profit research and advocacy organisation Algorithmwatch maps the use of automated decision-making applications in the public policy sphere in Europe, looking at everything from algorithms used for grading in schools, to those used for distributing family benefits, identifying individual risk factors related to social exclusion in young adults, and helping judges understand trends arising from previous court rulings.[115]

Now, if big data and AI form the socio-technical infrastructure of the information ecosystem of a democracy, its procedures and its institutions, then data pollution can be considered an environmental problem that challenges its very balance. That is, while citizens' data waste/exhaust might not be useful to the commercial actors collecting and storing the data, the creation of data-intense socio-technical infrastructures can and has often been repurposed, for example, to enforce mass surveillance activities of states and to provide asymmetric access to the data on citizens that can be transformed into black box manipulation of voter behaviour during elections.

As one of the instrumental EU policymakers behind the EU General Data Protection Regulation (GDPR), Paul Nemitz, argues, the accumulation of digital power that shapes the development and deployment of AI is a threat to the human rights, democracy and rule of law that are the cornerstones of liberal constitutions.[116] Several examples can be provided to illustrate the adverse impact of data pollution in the domain of modern constitutional democracies. The Cambridge Analytica scandal is the most famous. It revealed a British consultancy firm's use of machine learning to analyse the data of 87 million people worldwide to influence democratic processes in the US and the UK.[117] The Artificial Intelligence and Democratic Values Index (2021) issued by the Center for AI and Digital Policy (CAIDP) assesses AI adoption and policy strategies in 50 countries worldwide in terms of their democratic impact. It mentions the adverse effects of AI on the social environment, such as China's use of AI to score citizens in terms of their alliance to the state, and to control and target ethnic minorities and protesters as *the source of widespread fear and scepticism*.[118] Other examples are 'infrastructural' in nature (see the Infrastructures Domain) when facial recognition systems in countries from Austria to the US are embedded in public spaces and used for surveillance purposes, or when AI is used for predictive policing, thereby predetermining human destinies based on historical data.

> *During the pandemic, the digitalisation of politics accelerated. Before that, we felt the effects of data pollution in the US presidential election in 2016 with Cambridge Analytica and Donald Trump's election. We saw how a software program could influence choices and the ballots by targeting individuals with personalised ads. We also understood that data protection is not only about privacy protection; it is also about the public sphere and we have seen that its impact can take form in terms of private, public and even global harm. It can actually damage an entire political and electoral political system and our democracy.*
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> - Sebnem Yardimci-Geyikci, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

4. Human Rights

In terms of human rights, data pollution constitutes a corrosion of the international system that protects the rights of people everywhere. International human rights as we know them today were developed, institutionalised, standardised and embedded into international agreements, laws, procedures and practices over decades. Nevertheless, in the past ten years, not only was the legal implementation of human rights challenged in the context of emerging ICTs and the development of a digital sphere, but the very justification of specific human rights, such as the right to private life, has been questioned. International human rights have their origin in the UN Declaration of Human Rights (UNDHR) that was drafted by representatives from regions worldwide and proclaimed in 1948, in addition to other international instruments, treaties and covenants. Furthermore, the European Convention of Human Rights (ECHR) was signed by 47 member states and entered into force in 1953. Mechanisms are in place for monitoring the compliance of state parties to the UNDHR with their human rights obligations, while ECHR signatories are accountable to the European Court of Human Rights (ECtHR). In the EU, the Charter of Fundamental Rights, which came into force in 2009, further embeds the rights of EU citizens in EU law. Here, the protection of personal data (article 8) as a fundamental right of EU citizens is also delineated in an extensive data protection regulatory framework (the GDPR).

The development of BDSTIs in the late 1990s to early 2000s was enabled by the accumulation, centralisation and tracking of digital data across geographical territories and legal jurisdictions. As they were integrated in society, individual human rights protections were increasingly challenged and held up against interests of, for instance, states to control and gather intelligence, or the interests of data-based business models of internet platforms. Arguments against the right to privacy were legitimised by invasive state and business practices. In this way, privacy *got a bad name for itself*[119] and was at one point even described as *no longer a social norm*.[120]

Data pollution in the human rights domain amounts to a gradual corrosion of the environment of an established human rights system. The ECtHR has on several occasions interpreted and made decisions on the challenges that the progress of digital technologies pose to the ECHR's territorial definition of jurisdiction.[121] In 2013, following Edward Snowden's revelations of a mass surveillance intelligence global system, the United Nations General Assembly even had to reaffirm that the same rights that people have offline must also be protected online.[122]

Nevertheless, international human rights are also gaining a foothold as instruments for citizens and citizen advocacy organisations to formally challenge and hold accountable the entities responsible for environmental problems that are directly affecting human health and well-being. For instance, although the ECHR does not contain a specific right to a healthy environment, environmental issues that affect the rights of people, such as the more traditional forms of pollution (e.g., industrial emissions and hazardous waste) **are** increasingly being brought before the ECtHR.[123] Similarly, data pollution issues that affect individual rights are also increasingly often being legally challenged as part of a human rights framework. Famously, in 2013 following the Snowden revelations, Austrian lawyer and founder of NOYB Max Schrems filed a complaint with the Irish Data Protection Commissioner stating that Facebook Inc. (today renamed as Meta Platforms Inc.) was illegally sharing his personal data with the US. This case led to the invalidation of the Safe Harbour data-transfer agreement between the EU and US, which is still being renegotiated today.[124]

Data pollution and AI pollution is about the deterioration of human rights on an intra-generational as well as intergenerational scale. Under this umbrella of data and AI as a deterioration of human rights, we can think of data ethics. There is a list of ethical issues related to the data life cycle of AI. How data has been collected, how it has been acquired, how it has been sourced, how it is stored, how it is been labelled.

- Aimee van Wynsberghe, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

5. Infrastructure

Our personal, social and natural environments are increasingly extended and transformed by BDSTIs and AISTIs (see glossary). The social environment is sustained and altered in and by social networking platforms that extend real-life social relations. The same happens in the personal environment when identity is expressed in profiles and feeds or accumulated through profiling algorithms. Moreover, the natural environment is transformed and extended by constantly evolving socio-technical infrastructures.

In this regard, we can think of the way in which the personal, social and natural environments of our global society have evolved. In the modern world, reduced travel times and costs shorten the distance between different places and the development of global means of communications (from the telegraph to the World Wide Web) has transformed human experience and representations of time and space. This has amounted to an *annihilation of space through time* that has transformed the very objective qualities of time and space.[125]

Essentially, different types of socio-technical infrastructures (such as BDSTIs and AISTIs) are the 'human' components of the environment.[126] What this means is that humans actively invent, create, design and repair socio-technical infrastructures, and they also negotiate, compete with and exercise power over it.[127] The infrastructure that shrunk the globe, from railroads to information highways, was made by humans and, as such, it is imbued with human controversies and interest negotiations, which many times throughout history has resulted in the domination of one people and social group over another. Infrastructure is made up of sites of human power struggles and social conflicts[128] invested with different visions and hopes regarding the human occupation of space.[129]

As argued elsewhere, AI and big data have become the socio-technical infrastructure of power and access (AISTIs and BDSTIs) in society today:

The computer hardware and software of the AI systems that store and handle big data are embedded in society and, like bridges, streets, parks, railroads and airways, they form our spatial environment, although they are different from traditional infrastructures. Roads and bridges, for instance, form the basic material architectonics of society and thus provide or limit access to places, but they are passive, so to speak, when mapping and expressing human motives, morals and social laws. AISTIs transform the very objective material qualities of space. Quite literally they transform space into interconnected digital data [...] AISTIs also lock us in specific positions, providing or denying access based on the processing of personal data. They are mediating spaces.[130]

The human infrastructural power component of personal, social and natural environments can also be affected by data pollution. And, just like air pollution, where human exposure is increased by the concentration of pollutants in the air, the adverse human impact of data pollution is increased by the concentration of data pollutants in BDSTIs and AISTIs.[131] The *space of flows* of the network society consists of electronically linked places dominated by *managerial elites*.[132] That is, power is distributed in the very design of information infrastructures and thus data pollution emerges when the concentration of data power in specific 'places' in socio-technical infrastructure is high and adversely impacts the power distribution between different actors in society.

In previous sections, the accumulation and concentration of data possession, storage and access has been illustrated to negatively impact our social and personal environments in terms of chipping away at human rights (such as the right to privacy) and democratic societies. However, what is less obvious is that it also changes the natural environment in terms of response and mitigation when, as mentioned above, it affects a granular analysis of the carbon footprint of major AI models on a global scale, as regional data centre statistics can only be derived from the *managerial elites*.[133]

> *Issues to consider in relation to AI sustainability are therefore who has access to data and data collection, which is currently very asymmetrical, for designers and scientists, but also for governments and companies that are not part of the big tech ecosystem. The idea of pollution is associated with something that is excessive, something that by its sheer size and volume is damaging. How can that damage be better controlled? If not through size, then it should be through other means.*
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> - Carolina Aguerre, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

6. Decision-Making

Data pollution in the design of autonomous or semi-autonomous decision-making systems can have adverse impacts in the human decision-making domain. In the realm of everything from civic participation to social networking, judicial practice and many others, decision-making is increasingly extended by components of machine learning data analysis (also referred to as ADM Systems) that create evidence for, support, and/or replace the process of arriving at a point in which a decision can be made, often even making the decision itself.

The effects of data pollution in the human decision-making domain are most profoundly expressed as the reinforcement or creation of bias and discrimination in society. Friedman and Nissenbaum explored bias in the design of early 1990s computer systems supporting decision-making processes in various domains.[134] They illustrated how computer systems unjustly benefitted or put some groups at a disadvantage, and developed three categories with which to discern bias in the design of systems:

Pre-existing bias comes from the outside of the computer system. It can be individual or social, and it already exists in social contexts and in the personal biases and attitudes held by the developers of the system. This type of bias is embedded in a computer system either explicitly and deliberately or implicitly and undeliberately by institutions or individuals.

Technical bias comes from technical constraints or limitations, like imperfections in pseudorandom number generation that, for example, systematically favour those at the end of a database.

Finally, *emergent bias* appears in the context of use of a computer system.

We might similarly address the data pollution of decision-making environments as a simultaneously social and technical component of the very data design of an ADM system embedded in a decision-making environment: An ADM system trained on an existing societal language and discourse (for example news articles) pollute a socio-technical decision-making environment when 'existing bias' in society is reproduced in the ADM system. Bolukbasi et al. (2016), for instance, found that the 'word-embedding' machine learning methods that are most commonly used for language processing in online search engines were reinforcing societal gender bias because they were trained on Google news articles. Words such as architect, philosopher, financier and similar titles were grouped together semantically as *extreme he* words, whereas words such as receptionist, housekeeper and nanny were grouped together as *extreme she* words.[135]

Similar data pollution in the decision-making domain may also happen when minorities are not included in data design teams and when their interests are not reflected in data design or generally when the developmental phase of AI is framed within specific cultural contexts.[136]

Data pollution can also emerge as a 'technical bias' of, for instance, a data classification system that fails to include representative data on minority groups. In one recent example, a study of patients in Boston (USA) revealed how an ADM system used to score the health status of patients waiting for a kidney transplant assigned healthier scores to African Americans on the list (thereby potentially affecting decisions regarding their eligibility for a transplant), as it was including race as a category in the design of the system.[137]

Finally, socio-technical decision-making environments may be polluted when biases 'emerge', as ADM systems begin to take precedence over human decisions. For example, when exams were suspended due to the COVID-19 pandemic in the UK in 2020, the

British exam board, Ofqual, deployed an algorithm to generate student grades. This meant that teacher assessments of each individual student were replaced by an algorithm, which took into account their school's performance in the past. The result was that the grades of students from large state schools decreased, while the grades of those attending smaller fee-paying schools increased.[138] In another context, the Dutch digital welfare fraud detection system SyRI (Systeem Risico Indicatie) was used to detect the likelihood of an individual committing tax or benefit fraud by analysing large data sets from different sources. Discrimination emerged quite clearly when the system was deployed primarily in low-income neighbourhoods.[139]

In the human decision-making domain, we may suggest to consider two forms of data pollution:

• *Intentional data pollution*

In the development of machine learning systems, data pollution is traditionally associated with training data that causes the system to learn an incorrect model, resulting in the misclassification of samples or actions that run contrary to set objectives. Data pollutants can be intentionally inserted in training data with malicious intent. For instance, Microsoft's AI chat bot Tay (released on Twitter in 2016) was trained on interactions with people on Twitter. It suddenly started posting offensive tweets and had to be shut down. Microsoft claimed that Tay had been 'attacked' by internet trolls with offensive language and had evolved based on these interactions.[140] Intentional data pollution does often not result in the data pollution of decision-making environments, as the polluted system simply will not work according to set objectives and is thus never deployed in practice—or only deployed shortly, as was the case with Microsoft's Tay.

- *Unintentional data pollution*

The greatest impact on the human decision-making domain is most often the result of unintentional data pollution. That is, when 'pre-existing' social and individual bias are embedded in the data design of ADM systems, in training data or by non-representative development teams, or when bias 'emerges' after the ADM systems have been embedded as normative socio-technical infrastructure in human decision-making domains. In these cases, the reproduction and reinforcement of the bias of an ADM system will result in discrimination against individuals or groups in the specific domain.

There are several examples of decision-making domains being affected by data pollution. The most profound effects are found in examples where AI systems and tools are adopted and implemented as normative socio-technical infrastructures, taking precedence over human decision-making processes. For example, a report on algorithmic bias by a group of researchers from the University of Chicago states that biased algorithms are deployed throughout the US healthcare system, generally having an influence on decisions about how patients are treated by hospitals, insurers, etc. Such ADM systems are often allowed into the decision-making domain of healthcare without vetting and oversight and have been used for decades without assessment of their ethical impact.[141] [142] Another such example is the mobility service Uber's 'robo-firings'. The company employs algorithms to discover fraudulent activity by drivers, firing them without human intervention. Several such cases have illustrated unchallenged errors and their very real human consequences. In 2020, four drivers in the UK and Portugal who had been dismissed based on decisions made by the algorithm filed suit against Uber, claiming that algorithm-based firing violates Article 22 of the GDPR, which establishes a prohibition of decision-making based solely on automated processing.[143]

Particularly, the human(-centric) approach stands out in the data pollution decision-making domain as an approach that ensures the development of socio-technical infrastructures of human empowerment that involve human life, experience and critical empowerment in the very data design, governance, use and implementation[144]. As illustrated by Pasquale with a number of case studies in health care, education and media focusing on his first law of robotics AI, complementing rather than replacing human expertise realises important human values.[145]

> *Take, for example, the introduction of bias in our data sets. When data sets under-represent a minority group, because they were not included in trials. When you set up a research study or a trial, you will have very strict parameters for who will be included in each trial and it is rarely the most ill patients, the elderly or the homeless, for example. The ones we need to help the most are often the least represented. When algorithms are made, based on historical 'medical facts' from these studies, these population groups will not be represented.*
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> - Signe Daugbjerg, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

7. Global Opportunities

Building inclusive and sustainable economies and societies on a global scale by creating global opportunities is an ambition rooted in the UN Agenda on Sustainable Development. However, this ambition is being hampered by data pollution. Data pollution in the global opportunities domain is 'data colonialism', as it reinforces existing social hierarchies and colonial power dynamics that impact the distribution of global opportunities.[146]

Uneven world power dynamics, geopolitics, territorial expansion and globalisation processes have, throughout history, shaped the opportunities (or lack thereof) of nations and people. Likewise, although they offer new economic and social opportunities, unbalanced processes of digitalisation have reinforced divides between the Global North and the Global South from the outset. Accordingly, the first global summit on the information society, the 'World Summit on the Information Society' (WSIS), was established at the UN General Assembly in 2001 with the stated aim to develop and promote an inclusive global information society, and enable the opportunities of new ICTs for all and address emerging digital divides.[147] Nevertheless, today in 2022 it is evident that the big data and AI 'revolution' has made the greatest difference in terms of opportunities in the economies of developed nations, while developing nations are being left behind. At the same time, the very experience and impact of data pollution are most profoundly experienced in communities that have traditionally been the most exposed in terms of global power dynamics. Existing inequalities rooted in a colonial history are replicated and reinforced in the new digital data systems of power, with data pollution most profoundly impacting already-vulnerable communities once again. Browne, for instance, describes the African American experience of digital surveillance as *nothing new*.[148] In fact, it builds on histories of being subjugated to acts of surveillance, violent branding and control. Cieslik and Margócsy similarly describe the creation of datafication infrastructure during the colonial period as the foundation of modern day asymmetries of power replicated in systems of datafication.[149] They refer to cases in which data resources are extracted from the Global South to be analysed in the Global North, often exploiting the insufficiency of legal frameworks in the protection of the rights of local citizens.[150]

Data pollution is *data colonialism*, a *colonisation* and *commodification* of everyday life,[151] and a component of new forms of *digital colonialism*[152], that is, the constitution of global power dynamics and geo-politics in which technological dominance creates the political, economic and social domination of some nations and peoples, or some communities, over others. It is a form of colonialism that is therefore also actively resisted in local communities and regions affected by it.[153]

In this regard, we may describe data pollution in the global opportunities domain much like Mejias and Couldry describe data colonialism as a type of global exploitation of people and resources:

Instead of territories, natural resources, and enslaved labour, data colonialism appropriates social resources. While the modes, intensities, scales and contexts of data colonialism are different from those of historic colonialism, the function remains the same: to dispossess.[154]

In continuation of this line of reasoning, with an emphasis on the specific socio-technical evolution of AI, Mhlambi describes AI colonialism as a *colonising impact* shaped by dependencies.[155] AI implemented in the Global South is developed primarily by outside companies and thus exacerbates imbalances in the distribution of power and resources—for instance, when ADM systems implemented in local contexts reflect Western values only. A series of articles in MIT Technology Review by senior AI Editor Karen Hao et al illustrates this new form of AI colonialism in case studies in which the implementation of AI *repeats colonial orders*.[156] In South Africa, AI surveillance tools reinforce digital apartheid and racial hierarchies; in Venezuela, AI industries exploit cheap labour for data-labelling, and in Aotearoa (the Māori name for New Zealand), language models trained on dominant languages are being challenged by an indigenous couple and their non-profit radio station. Hao describes AI colonialism as a new form of colonialism similar to the European variety seen starting in the 16th-century expansion and 'discovery' of land. Though they are different, they are both driven by profit and power interests:

The AI industry does not seek to capture land as the conquistadors of the Caribbean and Latin America did, but the same desire for profit drives it to expand its reach. The more users a company can acquire for its products, the more subjects it can have for its algorithms, and the more resources—data—it can harvest from their activities, their movements, and even their bodies.[157]

Data pollution in the 'global opportunities domain' is an adverse effect that reinforces existing power imbalances in global society across different levels. The early efforts to address global inequalities and to create a more-balanced information society in the development of WSIS processes in the early 2000s have now evolved into the development of regional laws and requirements. This is particularly true in Europe, where a tough legal stance on data protection, the Digital Markets Act (DMA), Data Governance Act (DGA), Data Act (DA) and Digital Services Act (DSA), and a new AI Act proposal are laying down rules and requirements for digital platforms and developers, turning the region into a ‘regulatory super power’. As described in Chapter 2 of this report, worldwide recommendations, policies and strategies are addressing the ethical and social implications and sustainability of AI. New responsibilities arise for companies and developers, lawmakers and citizens. However, what is often not accounted for in these global risk mitigation strategies (dictated by the institutions, civil organisations and companies of Western developed economies) is that countries and regions have moved at different speeds and exist in different stages of global ICT and digitalisation. Developed countries are historically responsible for the majority of data pollution in the personal, social and natural environment. However, this is not accounted for when asking developing countries (which are just now catching up in the global ICT race) to shoulder the burden of newly established responsibilities and compliance.[158] Thus, the global response to data pollution not only constitutes a response to unequal opportunities and global power dynamics. It is in and of itself a form of power that may even reinforce existing global opportunity divides between regions, countries and peoples. Global coordinated responses to data pollution represent the power to identify problems and design their solutions, the power to implement them and at what speed; the power to set priorities that correspond with the cultural and economic context and capacities of, for instance, developers and citizens. It is a power that most often comes with the loudest voice and the greatest existing force backed by more resources, and political and economic power. But it also comes at the expense of other less powerful voices in the global context. In this way, not only does data pollution reinforce the position of those already at the greatest disadvantage by replicating existing asymmetries of power; in our data pollution mitigation strategies, we risk further bolstering these divides.

My first attempt is to look at sustainability from the 2030 Agenda with its 17 SDGs, 169 targets and 232 indicators, but more importantly to look at the gaps that emerge from a data pollution lens in this programme. There is a need to assess how affected and disenfranchised/marginalised communities may be able to devise their own ideas as to what data about them and their environment should be and look like.

- Carolina Aguerre, Data Pollution & Power Group, 2nd Meeting Mini Report, 2021

The majority of the costs are hidden from us. They are in the backyards of vulnerable communities. They are hidden from us because we don't live with those consequences every day. Here, I think there is also a risk of imperialism. India and Africa are trying to get into the AI space and they look at the European Commission or the United Nations ethical guidelines for AI. And they say: you have had all this time to develop your AI and models and data and now you are telling us that we have to do it in this ethical way. What is the solution to that? Because in this way we are accelerating digital divides all over again.

- Aimee van Wynsberghe, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

8. Time

Data pollution can have damaging effects on various forms of space. For instance, it may damage social spaces, altering the spatial outline of the information architecture of modern liberal democracies; it may damage the physical space of our natural environment with greenhouse gas emissions; or it may intrude on the protective layers of our personal spaces. However, the very temporal constitution of our natural, social and personal environments can also be polluted with data. The data design and classification models of AI will always only take into account what is useful to the system, i.e., the specific interest the system is designed for. In this way, AI systems may ultimately reduce dynamic cultures and multiple experiences in the interest of the AI model. Qualitative pasts and multiple futures do not make sense in and by themselves in AI systems.[159] The Ofqual algorithm mentioned before, for example, reduced students' personal qualitative lives and performances to the effect of their schools' historical performance. AI tools developed for judicial systems are another example: created to support a judge's decision, there are AI systems that process case law and then present a summary decision. When systems such as these become normative in judicial contexts, privileging the quantitative AI analysis of case law decisions over the qualitative contextual judgement of the individual judge, they also *lock his future choice into the mass of these "precedents"*, as one Council of Europe committee charter has described it.[160]

AI temporal rationality is a form of data pollution that limits human action and individual responsibilities. Most often it disempowers the experiences and voices of less powerful communities that are reduced to mere instantaneous data that the systems use and act on according to the dominant interests of society. For example: when minority groups are underrepresented in data used as the basis for decisions made on social benefits, when critical scientific medical analysis only benefits one privileged group, or on the other hand when a minority group is overrepresented in data in such a way that puts them at a disadvantage in society, such as data from specific city zones used for predictive policing.

Last but not least, it is important to consider the intergenerational dimension–what we do with data right now will affect the future. Or, to put it differently, we have power over the future with our current data practices, intergenerational balances. We are shaping society with our current practice.

- Pak-Hang Wong, Data Pollution & Power Group, 1st Meeting Mini Report, 2021

4.

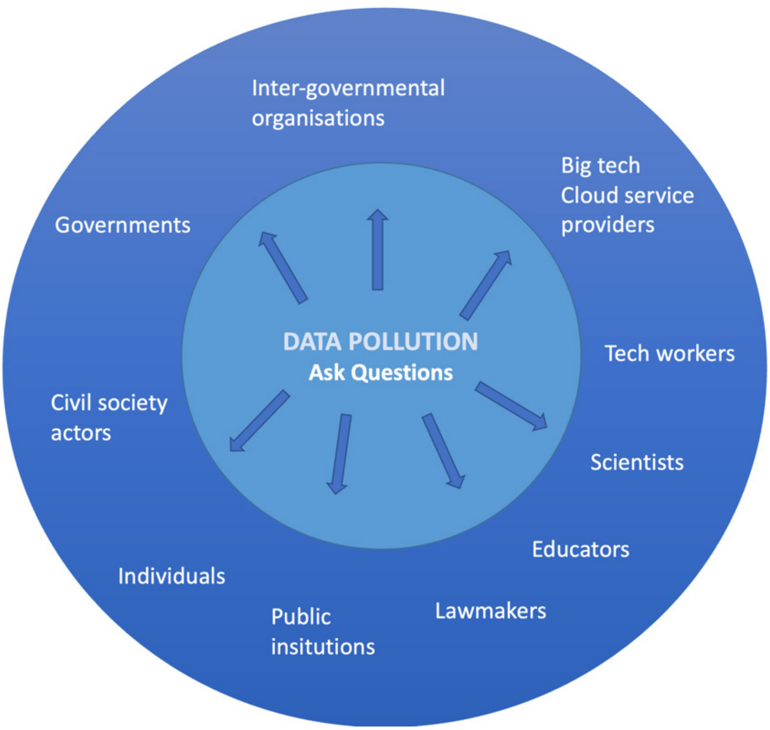
DATA POLLUTION QUESTIONS

PHILOSOPHER GILLES DELEUZE ONCE stated that *True freedom lies in a power to decide, to constitute the problems themselves*.[161] It is important to ask what kind of reality the problems we include in the global sustainable development agenda present and who has an interest in solving these specific problems. Who identifies the problem and who creates the solutions? Crucially, which and whose problems are not being considered? Who is left out of the 'problem solving' and 'agenda setting'? In other words, to solve an environmental problem for the planet and *for all* we need to also be ready to address new problems and ask new questions.

In an era of big data and AI innovation and competition, the adverse side effects of data pollution on our social, natural and personal environments are currently mostly addressed as isolated side effects within specific domains. They are not considered at large and together as components of socio-technical spaces of empowerment or disempowerment.

Stating data pollution as a problem is in and of itself a challenge to existing power dynamics and the questions we ask based on this new framing of an environmental problem will guide solutions and global societal engagement in mitigating the environmental impacts of AI data.

In this last section of the white paper, big data and AI are restated as environmental problems with questions that will open up a discussion about different aspects of data pollution in different domains and among various power actors. The questions were developed by the members of the Data Pollution and Power Group and edited by the author.



Data Pollution Questions

AI in Society

Whose narrative about the role of AI in society do our AI tools, science and conceptualisation serve? And who bears the greatest risk?

Is some environmental data pollution more acceptable than others? Should we differentiate between pollution in certain fields based on needs or importance? For instance, are CO_2 emissions from healthcare algorithms more acceptable than CO_2 emissions from use of social media, banking or shipping?

Who is responsible for solving and finding solutions to the different types of issues arising from the data pollution domains?

What does a coordinated response to the complexity of data pollution look like?

What is the current dominant viewpoint on data in AI science and innovation? Which views remain invisible?

Science, development and standard-setting

Who are 'tech workers'? How do their individual cultural, social and economic contexts and skill sets influence the data design of AI?

Can we describe the life cycle of AI for an environmental and sustainable impact assessment?

Should different measures be taken or considered for the training or development period of AI? If so, how can this be made explicit?

Can standards for data infrastructures incorporate a data pollution aspect?

How can we make data pollution that impacts the natural environment transparent? Which parameters should be included in a transparent CO2 analysis?

Is there a way to create a carbon footprint calculator that easily, transparently and affordably reports on carbon emissions, which can be compared within and across sectors?

What are the existing technological dependencies in society and for AI developers? Are there new dependencies arising that may increase data pollution in specific domains?

Who has an interest in the data of the design of a specific AI system? And how are these interests met by design? Are there conflicts of interests and how are they resolved by design?

How do we ensure equal representation of impacted population groups in AI data design? How do we ensure the transparency of baseline data used for calculations/predictions?

How are different AI methods related to different levels of energy consumption?

How do we redefine the value criteria for AI developers to include data pollution considerations?

What does a good AI model that is both efficient and sustainable look like?

Policy, law and international collaboration

How does the changing relationship between states and big technology companies impact politics? Does it require a new social contract and how will this new social contract be designed? What role will AI play in these new social contracts?

How do we make the data pollution problem more comprehensible to a wider field of policy makers?

How can the issue of data pollution be included in national, regional and international sustainable development policy and strategies?

What are the mechanisms for establishing a clearer link between big data/AI sustainability and the SDGs?

The development of data-sharing infrastructures for climate and planetary observation data with the use of AI technology is a key focus among world powers. Is there a way to assess the balance of the environmental benefits of initiatives as such, with their energy costs and impacts on the natural environment?

What can we ask from developing countries in terms of data pollution responsibilities and compliance? Do we need to develop a baseline for ‘survival emissions’ and ‘luxury emissions’?

Education

In many sectors, data pollution is not discussed or deemed important. What is the best way to raise awareness of the issue?

How do we change the conception of ‘just because we can develop it, we should’ to ‘do we really need this? How and when will it be beneficial? Who will it benefit?’

CONCLUSION
A Data Pollution Movement

THIS WHITE PAPER OUTLINES the connections between the different actors and components of a nascent environmental data pollution movement with 'sustainability' as the thread that links its elements in a shared understanding and approach. The main objective is to ensure that data pollution of AI in particular is included in the global sustainable development agenda.

Data pollution is an environmental problem with interrelated adverse impacts on our natural, social and personal environments. It is the unsustainable handling and distribution of data resources defined in a global society with power dynamics that are transformed, affected and even produced by interconnected streams of data. Data pollution reinforces and affects asymmetric power balances between actors on a local, regional and global scale. This is why we need a data pollution movement.

The data pollution movement is already taking form. In the policy and legal space several policy initiatives have recently been negotiated and put in place to address the sustainability and ethical implications of the adoption and implementation of AI and data-based systems and technologies. Governments worldwide and intergovernmental organisations have presented AI ethics principles and recommendations - several with a special focus on the sustainability of AI and the environmental impact. Since 2017, no less than 60 countries worldwide have adopted artificial intelligence policies.[163] The EU, in particular, has here taken the strongest regulatory position. Thus, a comprehensive European data protection regulatory framework was adopted in 2016 to harness threats to privacy and individual empowerment in an age of massive collection, storage and use of big data. In 2018 the EU's AI Strategy was adopted and in 2021 the world's first AI law proposal was published with a risk-based approach.[164]

Expectedly, in the tech industry, we have also seen **the emergence of new AI and data companies with an ethical agenda**, such as the Finnish privately-held AI lab Silo. AI, which builds human-centric AI solutions to support rather than replace humans in various work situations, all with the slogan 'AI for People'. Also, **larger, more established companies are increasingly differentiating their business practices with an ethical stance on data**. This includes consumer tech giant Apple, whose CEO, Tim Cook, for years used the argument that he 'sells products, not user data' to differentiate the brand from its Silicon Valley competitors. In this sphere, we also are seeing the emergence of AI ethics and sustainability claims and initiatives. Unfortunately, however, many activities in this sphere do not account for historical data pollution and thus advantages. They do not address the core structural power problems of technological dependency creation and data power centralisation. Moreover, while presenting sustainable data and AI practices in one domain, they continue data pollution practices in others while enacting no or very little real meaningful change.

In terms of technical data infrastructure, **the 'personal data store', 'trust' and 'stewardship' movement has been ongoing for a while now** among innovative entrepreneurs with the aim to shift data power asymmetries embedded in current data infrastructures. As a result, a range of new services that by default respect people's privacy and empower individuals with their data have been developed. The MyData global community includes organisations, SMEs, individuals and local networks working with the aim to: *... help people and organisations to benefit from personal data in a human-centric way. To create a fair, sustainable, and prosperous digital society for all.*[165] Many of these are challenging the privacy implications and CO2 emissions of an asymmetrical data economy that collects and stores data on central servers. They call for 'greener data' with a decentralized data trust model. Much is left to be explored both in terms of the basic functioning, interoperability and, last but not least, legal framework of data trusts and cooperatives, but the movement is growing and expanding.

Tides are changing in the sea of big data, and society is starting to understand and act on this shift. There is a sense of urgency to develop and implement an ethical and sustainable approach to data and AI, and the world's most advanced companies and governments are positioning themselves within this movement. Nevertheless, **we are still far from the kind of widespread societal awareness that will lead to real change**.

This white paper is a step in that direction. It explores the powers, interests and impacts of data pollution in eight domains, which can be summarised as follows:

Nature

Data pollution is a carbon footprint. It can be addressed in the design phase of AI as a component of the competences, practices, education and technological dependencies of AI practitioners. However, the extent and impact of data pollution is incrementally complex to measure and mitigation strategies are accordingly difficult to design and apply. We need a global coordinated response that recognises the power players shaping the contexts in which data pollution and its impact on the natural environment can be measured and tackled.

Science & Innovation

Data pollution is part of the culture of big data science and innovation. In a big data economy, the most powerful technology companies, institutions and accordingly also AI practices are dictated by the collective imagining of big data as an unlimited resource and opportunity. Tackling data pollution in the science and innovation domain requires a counter-balanced science and technology 'data sustainability culture' supported in policy, innovation and education. There is also a need for environmentally sound development strategies for alternative technologies.

Democracy

Data pollution is an imbalance in the information eco-systems of constitutional democracies. A democracy is founded on sensitive information balances between citizens and the State, which is stipulated in laws, state governance, institutional procedures and frameworks for the conduct of elected representatives and public servants. Modern democratic societies must ensure socio-technical infrastructure that reinforces and ensures the democratic ecosystem of information distribution between citizens, States and other powerful actors.

Human Rights

Data pollution is a corrosion of the international human rights system. As big data and AI socio-technical infrastructures (BDSTIs and AISTIs) are integrated in society, individual human rights protections are increasingly challenged and held up against, for example, the interests of nation States to control and gather intelligence, or the interests of the data-based business models of internet platforms. Fortunately, data pollution issues that affect people's rights are also more and more often challenged in court via human rights legal instruments.

Infrastructure

Data pollution is a concentration of data power in socio-technical infrastructure. Just like with air pollution, where human exposure is increased by the concentration of pollutants in the air, its negative effects are increased in correlation with the concentration of data pollutants in the socio-technical infrastructure of personal, social and natural environments.

Decision-Making

Data pollution is a bias in human decision-making with adverse consequences for individuals and society. Decision-making in the domains of everything from civic participation, social networking, judicial practice, etc. is increasingly extended with Autonomous Decision-Making Systems (ADM Systems). The human impact of data pollution in the various domains of human decision-making are most profoundly expressed as the reinforcement or creation of discrimination in society.

Global Opportunities

Data pollution is colonialism. It reinforces existing social hierarchies and colonial power dynamics that impact the distribution of global opportunities. The big data and AI 'revolution' has made the greatest difference in terms of opportunities in the economies of the Global North, while leaving the Global South behind. At the same time, the very experience and impact of data pollution are the most intense in communities and among people that have traditionally been the most exposed in local and global power dynamics.

Time

Data pollution is a disempowering rationalisation of time. The data design and classification models of AI only take into account what is useful to the system which is established by dominant interests in it. In this way, AI systems ultimately reduce dynamic cultures and multiple experiences. Qualitative pasts and multiple futures do not make sense in and of themselves in AI systems. Data pollution of time disempowers the experiences and voices of less powerful communities that are reduced to mere instantaneous data to be used and acted on according to dominant interests.

In conclusion, power is currently integrated in very real digital data architectures and, as is increasingly highlighted in public debate, it most often upholds the world's most powerful actors while putting others at a disadvantage. These asymmetries of power are hidden in the narratives shaping AI governance, business strategies, and even science and innovation that result in very different experiences of data pollution. This is why we need the data pollution movement.

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Data Pollution is to the big data age what smog was to the industrial age. Our response to data pollution will develop much like our reaction to traditional forms of pollution—just much faster and hopefully with dedication and great force. This white paper describes a nascent environmental data pollution movement. It frames data pollution in the context of powers and interests exploring eight domains in which data pollution has the greatest impact: Nature, Science & Innovation, Democracy, Human Rights, Infrastructure, Decision-Making, Global Opportunities, and Time. The main objective is to ensure that data pollution of AI in particular is included in the global sustainable development agenda.

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