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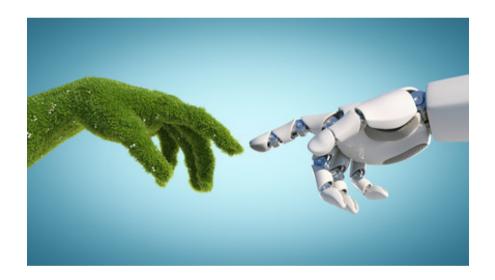
The role of Artificial Intelligence in the European Green Deal

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Abstract

Artificial Intelligence (AI) can be deployed for a wide range of applications to promote the goals of the European Green Deal. However, adverse environmental impacts of AI could jeopardise the attainment of these goals. The report describes environmental potential, clarifies characteristics and causes of environmental risks, and outlines initiatives and best practices for environmental policies. It illustrates the need for regulatory action to align design and deployment of AI with the goals of the European Green Deal and concludes with specific recommendations.

This document was provided by the Policy Department for Economic, Scientific and Quality of Life Policies at the request of the Special Committee on Artificial Intelligence in a Digital Age (AIDA).

CONTENTS

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AIDA	Special Committee on Artificial Intelligence in a Digital Age
ARIMA	Autoregressive integrated moving average
BAU	Business as Usual
BCG	Boston Consulting Group
CART	Classification and Regression Tree
CED	Cumulated energy demand
CEF2	The Connecting Europe Facility
CH$_4$	Methane
CO$_2$	Carbon dioxide
CODES	Coalition for Digital Environmental Sustainability
DEP	Digital Europe Programme
DNN	Deep neural networks
DVD	Digital Versatile Disc
EC	European Commission
EGD	European Green Deal
EIA	Ethical Impact Assessment
EO	Earth observation
ERTM	European rail traffic management system
ESA	European Space Agency
EU	European Union
FAO	Food and Agriculture Organization
GEO BON	Group on Earth Observations Biodiversity Observation Network

GHG	Greenhouse gas
GIS	Geographic information system
GPU	Graphical Processing Unit
Gt	Gigatonnes = 10^9 tonnes = 1,000,000,000
ICT	Information and communication technologies
IEA	International Energy Agency
INSPIRE	Infrastructure for Spatial Information in the EU
IoT	Internet of things
IP	Internet Protocol
ITU	International Telecommunication Union
JRC	Joint Research Center
LR	Linear Regression
LTER	Long Term Ecological Research Network
M2M	Machine-to-machine communication
MILA	Montreal Institute for Learning Algorithms
ML	Machine learning
MS	Member States
Mt	Megatonne
NASA	National Aeronautics and Space Administration
NEON	National Ecological Observatory Network
NLP	Natural language processing
NTNU	Norwegian University of Science and Technology
OECD	Organisation for Economic Co-operation and Development
PAWS	Protection Assistant for Wildlife Security (software)

PC   Personal computers

SARDA   Spot and Runway Departure Advisor

SARIMA   Seasonal autoregressive integrated moving average

SDG   Sustainable Development Goals

SVM   Support Vector Machine

TPU   Tensor Processing Unit (application-specific integrated circuit, to accelerate the AI calculations and algorithms)

TWh   Terawatt-hours

UK   United Kingdom

UNDP   United Nations Development Programme

UNEP   United Nations Environment Programme

UNESCO   United Nations Educational, Scientific and Cultural Organisation

UNICEF   United Nations Children's Fund

UNOSAT   UNITAR's Operational Satellite Applications Programme

US   United States

VAT   Value-added tax

LIST OF FIGURES

EXECUTIVE SUMMARY

Background and goal of the study

The European Green Deal pursues ambitious environmental goals which require a green transformation of many sectors of society. The transformative potential of Artificial Intelligence (AI) to contribute to the achievement of the goals of a green transition have been increasingly and prominently highlighted. At the same time, digital technologies such as AI considerably increase energy and resource consumption and create risks of adverse environmental effects. This ambiguous picture illustrates that political and regulatory action is necessary to channel the potential of AI towards the goals of the European Green Deal. Tailoring and implementing effective AI policies presuppose a solid understanding of the socio-technical mechanisms that may lead to desired or undesired consequences of AI. This report aims to contribute to the development of such an understanding.

Main findings

The report illustrates the potential of AI to achieve a green transition in several fields of environmental policy:

- A range of promising cross-cutting use cases can be differentiated: AI and other technologies have enormous potential, as they enable and accelerate the analysis of large amounts of data to increase our knowledge base, allowing us to better understand and tackle environmental challenges. The combination of Earth observation data with AI offers more effective, efficient and timely monitoring of environmental impacts and trends, brings new insights in the understanding of driving forces and environmental impacts and strengthens predictive capabilities. Thus, AI will produce information relevant for environmental planning, decision-making, management and monitoring of progress of environmental policies. AI-generated information could also help consumers as well as businesses to adapt towards more sustainable behaviour. Automated steering mechanisms and technologies enabling predictive maintenance will increasingly optimise a safe operation of infrastructures.

- Potential of AI can also be identified for various important sectors of a green transformation. AI applied to monitor and optimise energy consumption can support the integration of renewable energies in the electricity grids and has the potential to support key priorities of the Green Deal in the buildings sector. Applications in agriculture may allow for more efficient use of water, pesticides and fertilisers and thus could mitigate environmental impacts. The same is, in principle, true for the transport sector: AI-based methods are already used for improved planning of transport systems and infrastructure, to increase engine efficiency, optimise charging of electric vehicles, for the coordination of different transport modes or the control and management of railway systems. Use cases of AI also include opportunities to strengthen the circular economy, i.e. by making eco-design more effective or by assisting in the inspection, sorting, separation and disassembling process to circulate materials in the economy. The illustrated use cases exhibit AI applications to support adaptation to climate change and to fight pollution, as well as tools helping to preserve biodiversity and foster nature conservation.

On the flipside of these promising use cases, however, adverse impacts of AI must be considered:

- Direct negative environmental effects of AI result from the use of digital hardware and infrastructures such as data centres and networks. This leads directly to the increased consumption of material resources and energy. It is currently not possible to determine the proportion of energy consumption caused by the operation of AI in digital hardware, data

centres and networks. Given the increasing relevance of AI technologies and their heavy use of data, their contribution to the energy consumption of information and communication technologies (ICT) is likely to rise significantly. Data traffic in digital networks and other ICT consume about 7% of the world's electricity today, and the share is projected to increase to 13% by 2030. It has been estimated that 5-9% of the world's total electricity use is caused by ICT, which may rise to 20% in 2030. Greenhouse gas emissions (GHG) from global data centres and communications networks are estimated at 1.1 to 1.3 Gt CO_2eq in 2020. The future contribution of AI to GHG emissions will depend on the energy efficiency of data centres and their operation with renewable energies. Furthermore, it is crucial to make energy and resource efficiency a dedicated development goal in the AI innovation process.

- Systemic effects, e.g. rebound effects, evolve as consequences of intended or unintended changes in the behaviour of consumers, users or producers. Such effects can be the consequence of opaque dynamics of AI system learning and may be unintended and even run contrary to an intended environmentally friendly function of an application. For example, products designed to automatically manage and implement more efficient energy consumption may actually have the effect of causing users to give up control over their energy consumption and over-consume. The assessment of such effects can be challenging. However, recent studies prove that an assessment is, in principle, possible. A better understanding of the pathways and dynamics by which input is processed in AI-based decisions might help to tailor adequate regulatory measures. Environmental policy and research should therefore focus on further assessing the systemic effects of AI. Other adverse environmental impacts result from AI applications that, as a consequence of their intended employment, contribute to GHG emissions and nature destruction, e.g. the use of AI to unlock oil and gas deposits and to explore and develop new territories for fossil fuel extraction.

- The recent proposal for a European 'Artificial Intelligence Act' (European Commission 2021c) supports an EU internal market for secure trustworthy and ethical AI systems and establishes a governance system and enforcement related to fundamental rights and safety. The regulation will establish a list of prohibited AI and specific rules for AI systems with high risks to health, safety or adverse impacts on fundamental rights. However, these risks do not include any hazards related to the environment unless adverse environmental impacts pose a direct threat to human rights or interests. Rules in relation to data and data governance, transparency, human oversight and security do not yet provide a governance system that will avoid adverse environmental impacts. As a key recommendation, the report suggests further research and development of methods and institutional procedures for assessing and controlling environmental risks caused by AI.

- The EU strategies and policies related to AI already put a strong focus on the objectives of the European Green Deal, in particular the European data strategy with its plans for a specific 'Common Europe Green Deal Data Space' and the initiative 'GreenData4All'. The targeted programmes, in particular the Digital Europe Programme (DEP), the Connecting Europe Facility (CEF2), Horizon Europe and the Space Programme aim at boosting investments in AI research, innovation and adoption with a target of annual €20 billion in AI-related investment from the public and private sector after 2020.

- Without proper steering, there is the risk that AI-based research with potential to contribute to a green transition may not be prioritised if their expected economic benefit is not high. It is important that EU research programmes provide resources for potential AI applications in environmental areas.

- The analysis of Member States' AI strategies showed that only six Member States have included a strong focus on AI applications for the Green Deal objectives. Despite the efforts of the EU's coordinated plan on AI, the analysis indicates that further coordination with and between Member States' strategies is still needed to achieve the required impacts.

- Most of the international initiatives around AI do not sufficiently consider the environmental dimension of sustainable development and the EU could fill this gap.

1. INTRODUCTION

> KEY FINDINGS
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> Many examples illustrate the potential of AI systems and applications to promote the goals of the European Green Deal. However, there is also growing evidence of direct and indirect adverse impacts on the environment.
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> The use of AI as a catalyst for a green transformation requires intelligent political stewardship. Environmental policy and regulation should, first of all, focus on building better regulatory insight. This means creating knowledge in order to leverage technological potential in a well-targeted manner and developing procedures and methods to assess and mitigate environmental risks. Targeted funding for research and development is also required because it is unlikely that AI applications to support government activities related to monitoring, planning or infrastructures can be developed without public funding.

1.1. The research question: the role of AI in the European Green Deal

This study assesses the potential role of AI systems with respect to the European Green Deal (EGD). The EGD intends to promote fairness and prosperity and an efficient, competitive, and more sustainable economy for Europe. With respect to the environment, it targets no net greenhouse gas emissions by 2050, decoupling economic growth from resource use, preserving, and enhancing the EU's natural capital and protecting people's health and well-being from environmental risks and impacts. The EGD thus aims for a fundamental societal and economic transformation, which will have implications in all spheres of our societies and personal lives.

AI systems are increasingly permeating many aspects of our lives. A growing variety of data-driven, connected, and automated applications support us every day to navigate or communicate, to purchase goods or gather information. But AI is not only increasingly ubiquitous in our private quotidian routines: The technology's potential to raise our knowledge, to manage processes more efficiently and thus to control and shape our environment is already being exploited today in all sectors of the economy, in science and policy making.

Addressing the relationship between the desired green transition of the EGD and the de facto transformation propelled through AI is urgent. The technology's potential for the environment is frequently highlighted: With applications in areas such as energy, agriculture, housing or mobility, AI can potentially help to reduce energy and resource consumption, support decarbonisation and advance the circular economy. AI could significantly speed up and improve environmental research to advance ground-breaking applications, e.g. in the energy or the mobility sectors. AI may also improve regulatory or political decision-making by means of the collection, analysis, and processing of vast amounts of data and help with the identification of complex patterns in the environment or social interactions.

However, just as AI can work as a powerful lever to achieve the goals of a green transition, it might also amplify detrimental dynamics and create new environmental risks. AI systems strongly drive the energy and resource requirements of digitalisation through their energy-intensive algorithms and the intensive use of existing and newly developed information and communication technology (ICT) devices and ICT infrastructure (i.e. data centres and data networks).

As an issue of environmental policy, this Janus-faced nature of AI and the importance of regulation can be well grasped by looking at its basic functionality: In a nutshell, AI systems are machine-based systems that can make predictions, recommendations, or decisions influencing real or virtual environments for a set of objectives (OECD 2021). By ensuring that these goals are implemented, AI systems fulfil a regulatory function (see Lessig, 2000). The "unprecedented capacity" of AI (König 2020) to realise specific objectives explains its importance for environmental protection and sustainable development policies: In view of the large number of decisions that are shaped or automatically made by AI systems every day and in innumerable social contexts, the question of whether these systems consider sustainability goals is central. The question of whether AI will deliver a toolbox for a sustainable future or rather function to accelerate social and ecological problems may thus be decided to a large extent by whether it can be governed effectively in pursuit of sustainability goals. The EU has recognised this political task and taken steps to address important strategic and regulatory issues[1]. It intends to explore measures to ensure that digital technologies, including AI, can accelerate and maximise the impact of measures to address climate change and protect the environment. At the same time, it highlights the need for the digital sector in Europe itself to focus on sustainability.

1.2. Analytical Approach

A green AI policy can be understood as the endeavour to **"regulate (autonomously) regulating systems" along socio-ecological objectives**. From an environmental policy perspective, unlocking the potential of AI for the green transition requires answering two interrelated questions: First, what are the effects of an increased use of AI systems on the natural environment and developments such as anthropogenic climate change? We thus need to understand how AI systems define the goals and functions they implement. Second, what are effective pathways for regulation and governance to manage the dynamics related to AI in implementing environmental objectives?

In approaching these two questions, we first describe and structure the potential of AI to support the goals of the European Green Deal, ranging from the cross-cutting functionalities and potential of AI for environmental policy objectives to concrete use cases. We then go on to describe potential negative environmental impacts of the development and use of AI and subsequently identify approaches for their mitigation. Given the policy focus of the analysis, an overview of planned or already implemented instruments to lever sustainability potential of AI and mitigate environmental risks is provided. Building on the previous work steps, we formulate a set of policy recommendations.

1.3. Conceptual issues

There is no universally recognised definition of AI. The term AI refers not to one single technology but comprises a set of diverse approaches, methods and technologies, which to different degrees and in different ways show intelligent behaviour in various contexts. According to the recent proposal for an **European 'Artificial Intelligence Act'**, AI systems refer to *"software that […] can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with"[2]*. As stated in the proposal "*AI systems can be designed to operate with varying levels of autonomy and be used on a stand-alone basis or as a component of a product,*

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[1] The European Commission has published a White Paper on "Artificial Intelligence: a European approach to excellence and trust" (COM(2020) 65 final) aiming to foster a European ecosystem of excellence and trust in AI and a report on "The safety and liability implications of Artificial Intelligence, the Internet of Things and robotics" (COM/2020/64 final).

[2] The EU Artificial Intelligence Act further defines the technologies and approaches used to develop AI systems. These are machine learning approaches including deep learning, logic- and knowledge-based approaches and statistical approaches, Bayesian estimation, search and optimization methods. See Article 3 para. 1 of the Proposal for a Regulation of the European Parliament and of the Council Laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act), COM (2021) 206 final, 21.4.2021.

irrespective of whether the system is physically integrated into the product (embedded) or serve the functionality of the product without being integrated therein (non-embedded)" (European Commission 2021c).

"Artificial intelligence" as such must be differentiated from the individual technologies that can be used to implement AI (Christen et al. 2020). A prominent example of such a basic or "general purpose technology" (Jovanovic and Rousseau 2005) for AI is machine learning. These AI technologies serve to realise a number of **basic functions** such as pattern recognition, prediction of behaviour, or syntheses such as the creation of speech (see Figure 1). **AI applications** refer to specific use cases of AI functions. The term '**AI system**' means a structured, context-bound combination of AI technologies and approaches for the purpose of achieving artificial intelligence.

Human decisions according to Christen et al. (2020) are crucial for the formation of the goals of algorithmic systems in three respects: First, human design decisions are involved in combining AI techniques into an AI system. Secondly, a human makes a strategic decision to use the AI system in a particular context (e.g. instead of a human decision maker). Thirdly, the 'tactical level' determines when and in what way human decisions may shape or control the results of AI decisions. This may occur through the involvement of humans in the decision-making process itself; for example in the sense that AI generates suggestions from which the human chooses and in this manner gives feedback on the basis of which the system can adapt (human in the loop; i.e. the systems have a function as decision support), or in that the human observes the system to a certain extent and has a veto function (human on the loop) (see Christen et al., 2020).

Figure 1:   Components of current AI systems

'**AI decisions**' thus are conclusions of AI systems with real-world implications that depend on human decisions at the level of system design (e.g. on which kind of (data-)input shall be used for the system and which AI technologies are combined), the strategic level (decision on deployment of the system) and the tactical level (shaping the interaction with the person using the system – e.g. by feedback to decision support systems) (Christen et al. 2020).

This analysis focusses on concrete applications of AI and their environmental impact. A systematic assessment of the technical and design implications of the respective AI systems is not feasible in the given context. With respect to the notion of environmental effects of AI, we rely on an established concept for the environmental assessment of ICT systems (Liu et.al. 2019) and differentiate, where necessary, between first, second and third order environmental effects:

- **Direct effects or first-order effects** occur along the lifecycle, i.e. the production, distribution, use and disposal or recycling of ICT products, such as mobile devices, network infrastructures or data centres.

- **Indirect effects or second-order effects** refer to all those changes in resource use and environmental consumption that result from the use of ICT in various application areas. One example of this would be the use of AI systems to make a production flow in industrial manufacturing more energy efficient.

- **Systemic effects or third-order effects** arise from the complex interactions between digital technologies and fundamental societal structures and relationships, such as lifestyles, organisation and forms of work, the energy system, consumption and production patterns, social participation opportunities, and many more.

2. OVERVIEW OF THE MAIN ASPECTS OF AI AND THE EU GREEN DEAL

2.1. The potential role of AI in enhancing the capacities to understand and tackle environmental challenges – cross-cutting issues

Developments in the field of AI are highly dynamic, with new and innovative use cases arising on a frequent basis. Economic actors remain the main drivers in the development of AI applications and comparatively few AI-based solutions currently aim to solve environmental challenges. However, there is an increasing number of such applications, which are intended, inter alia, to monitor environmental damage, increase resource efficiency and improve our understanding of the environment and climate. Research on the potential of AI to foster a green and sustainable transformation is also increasing. The following chapters will take a closer look at the most prominent (current) use cases of AI applications for environmental purposes.

2.1.1. Better information for relevant decision-making

Enhanced scientific knowledge on the environment is a key condition for understanding and tackling environmental challenges. Farley et al. (2018) differentiate between five types of data streams in this context: (a) the continuous delivery of data by remote sensors on Earth observing systems; (b) the aggregation of individual scientific observations and experiments into larger curated community data resources (e.g. Global Biodiversity Information Facility); (c) investment in long-term ecological monitoring networks at national to continental scales (e.g. LTER, NEON; INSPIRE); (d) the deployment of automated and inexpensive sensor networks (e.g. phenology cameras, wildlife camera traps, and temperature loggers) and, lastly, (e) data captured by citizens. AI technologies can play a role in all five data streams.

The following section take a closer look at the **role of AI in earth observation (EO)**, as this offers important new insights into many environmental problems. The EU's EO programmes such as Copernicus and New Space produce large amounts of environmental data and provide many opportunities for AI systems, such as a more effective, efficient and timely **monitoring of environmental impacts and trends**, identification of patterns in available data to **bring new insights in the understanding of driving forces** and environmental impacts and **strengthening predictive capabilities** related to complex interactions in the geo- and biosphere. Thus, the combination of AI and EO can produce information relevant for environmental planning, decision-making, management and monitoring of progress of environmental policies.

There is a wealth of examples from research projects which combine different AI techniques with EO data. The Digital Twin of Planet Earth project combines digital infrastructure with EO data and AI-enabled applications to build models of the Earth to provide an accurate representation of the past, current and future changes[3]. The digital twin Earth is meant to visualise, monitor and forecast human activities on the planet and to support policy priorities on environmental issues, e.g. climate change, environmental degradation, or urbanisation. The project BigEarthNet is using neural networks for land cover classification from Sentinel-2[4] imagery which is essential for monitoring purposes in agriculture and forestry (Sumbul et al. 2019). In the ExtremeEarth project deep learning is used to predict extreme

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[3] Further information on the Digital Twin of Planet Earth project can be found on the website of the European Space Agency. Available at https://www.esa.int/ESA_Multimedia/Images/2020/09/Digital_Twin_Earth.

[4] Sentinel-2 is a Copernicus Earth observation mission acquiring high spatial resolution images over land and coastal waters.

natural events such as floods, droughts or storms and to provide concrete tools such as water availability maps for selected agricultural areas for field level irrigation support (Koubarakis 2019). Several research teams are working on methods that combine AI and EO data to detect clusters of macroplastics in oceans to support plastic waste clean-up projects (Biermann et al. 2020). As part of the global initiative 'AI for good', Microsoft started the initiative 'AI for Earth' (AI for Earth 2021). The initiative provides open-source tools, models, infrastructures and data related to land cover mapping, species classification, camera trap image processing and geospatial datasets and nature conservation data. The intersection of AI and EO is a key area of AI applications for visual diagnostics and an emerging field for deep learning. A future step could be a hybrid modelling approach, coupling physical process models with the data-driven deep learning algorithms (Rolnik 2019). Recent research has produced some web-based toolkits addressing specific use cases, e.g. UN Global Pulse developed in cooperation with UNOSAT a web-based toolkit for UN agencies that helps to monitor fires, flood assessment or the impacts of cyclones.

Using AI techniques in EO requires **significant additional work for data preparation, the integration of physical principles into algorithms, the ground truthing of data** to validate products and for the **development of data sets to train AI algorithms, which is complex and time-consuming for EO parameters.** Currently, the lack of training data sets for EO applications is a limiting factor in AI applications and the potential of AI in EO is considered largely untapped (ESA 2018). While AI is frequently applied to analyse optical images, multispectral optical sensors used by satellites or data from radar or laser sensors require further work for the development of deep learning and related analytic techniques. The initiative 'AI4EO' was started by the Φ-lab of ESA's Directorate of Earth Observation Programmes with the aim of bringing together the AI and EO communities (AI4EO 2021). A first challenge organised by the initiative aims at developing AI-powered solutions to facilitate the downscaling of analyses and forecasts of surface concentrations of particulate matter (PM2.5) and nitrogen dioxide (NO_2). The TELEIOS[5] infrastructure designs and implements a virtual observatory infrastructure for EO data (Koubarakis 2020). The activities of the European Commission in this area are summarised in Section 3.1.

AI can help accelerate the process of scientific discovery and experimentation, e.g. **by learning from past experiments to suggest future experiments that are more likely to be successful** (Donti 2020). Examples in this area are AI applications promoting the development of technologies such as batteries or solar panels or supporting the development of new sustainable materials through AI enhanced shorter testing cycles and periods. AI can also help accelerate computationally intensive simulations and link those simulations with real-time data, which will also speed up planning processes. In the social sciences, social media data is already used for research purposes, avoiding reliance on lengthy interviews. In plant science, the area of phenomics combines AI, big data on plant phenotypes, genetic information, and environmental information to enable gene mining for favourable agronomic traits for faster crop improvement (Zhao et al. 2019).

2.1.2. AI applications to inform and encourage responsible business behaviour

Businesses have an impact on the environment both through their own operations as well as through their supply and value chains. AI can help businesses develop more sustainable business models.

Firstly, they can **provide better information on how to reorient economic decision-making toward sustainability**: E.g., inquiries of AI applications in financial technology ("Fintech") diagnose a range of

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[5] TELEIOS is a recent European project allowing scalable access to petabytes of Earth Observation data and effective knowledge discovery.

potential to better align financing decisions with sustainable development. A UNEP report analyses how technologies like machine learning could lead to "*revolutionary innovations for building trust, transparency and traceability for financial transactions and make tomorrow's financial system far more efficient in mobilizing green finance*". For example, Fintech is supposed to be able to disrupt the provision of financial protection, risk management, risk transfer and risk diversification for vulnerable and exposed communities, real economy assets and infrastructures, and nature's ecosystems (Castilla-Rubio et al. 2016).

AI applications can improve resource, energy and material efficiency. AI solutions in this field build upon Industry 4.0, i.e. the automation of manufacturing and industrial practices via the use of smart technology. Technologies such as machine-to-machine communication (M2M) and the internet of things (IoT) are linked to mechanical and electronic devices (production machines, industrial robots, etc.) and integrated for increased automation, improved communication, and self-monitoring. The creation of such a cyber-physical system leads to vast amounts of data which can be used, inter alia, to analyse and further improve processes or develop new products and business models. AI helps to unlock this potential via predictive analytics, intelligent assistance systems, robotics, intelligent automation, and intelligent sensors. Although Industry 4.0 solutions are usually developed and implemented to achieve cost reductions or other financial benefits, environmental opportunities arise when the use of resources, energy, and materials (i.e. waste) is effectively reduced (Seifert et al. 2018).

Adverse environmental impacts occur to a large extent within businesses' **supply and value chains**, e.g. in the context of sourcing minerals, the manufacturing of products or the disposal and recycling of waste. At the same time, more and more datasets are generated for each step along the value chain. As outlined above, businesses today are heavily instrumented with sensors, trackers, and other smart devices collecting data in real time. **If AI-supported Industry 4.0 solutions are being used to further the integration of data along the value chain**, they can allow for the tracking and monitoring of components and materials across their entire life cycle – a prerequisite for realising the transition towards a circular economy, among other things (Wilts and Berg 2017).

AI applications can also help businesses in selecting and monitoring their suppliers by more efficiently compiling and analysing unstructured data such as news entries, audit reports or social media postings. Moreover, AI solutions used by purchasing companies can indirectly benefit environmental performance among suppliers. For example, near real-time tracking of inventory as well as purchasing patterns allows for very accurate demand forecasts. Accurate forecasts in turn avoid short-time changes to orders, which may require air shipping, cancellation of orders or overstocking, both of which may result in the destruction of goods (Sanders 2019).

2.1.3. AI applications to inform and encourage responsible consumer behaviour

Information on where and how products were manufactured is considered critical in raising consumer awareness. AI can make such information readily available. For example, researchers in Germany are developing a 'Green Consumption Assistant', intended to facilitate sustainable consumption by providing information about sustainable alternatives when buying or searching for products online. The assistance system would inform on manufacturing conditions and energy usage, among other things (ZUG 2021).

In addition, AI systems could incentivise or 'nudge' consumers towards more sustainable consumption. Nudging has received widespread attention as an environmental policy instrument in the last years (Carlsson 2019). Combined with theories on human behaviour, partially automated (real-time) analysis of large amounts of data from various sources could help reduce ecologically harmful perceptual or behavioural structures and enable environmentally friendly purchase decisions (Michalek et al. 2015).

Successful AI assisted nudging has been observed in the hotel industry. Virtual assistant and robots were deployed as nudging agents to influence behaviour among hotel guests in relation to energy, water and towel use (Tussyadiah et al. 2019). The ethical implications of nudging as a "*subtle subversion of free will*" (Thapa 2019), however should always be considered.

2.1.4. Steering and maintaining technological systems, infrastructure or hazardous facilities

By means of enhanced sensory systems and automated data analysis, AI systems can enable a much faster and much more efficient management of technological systems and critical infrastructure. As an illustration for the promise of AI systems to anticipate and regulate complex interactions between social subsystems and natural dynamics, Thapa (2019) cites the example of the German applied research project WindNODE, "*which uses data analytics to increase the overall efficiency of renewable energy production by managing energy consumption. The system includes forecasts to predict the electricity generation of solar panels and wind turbines, which are coordinated with flexible energy consumers such as production lines that can run at different times or with commercial refrigerators that can be turned off for a few hours during times of low electricity production without significant temperature increases.*" In the EU-funded research project FUDIPO[6], for example, control algorithms were developed to improve the performance of a biological wastewater treatment plant, measuring the quality of incoming waste, and lowering the aeration demand. The latter reportedly constitutes about 50% of a wastewater treatment plant's electric energy consumption (FUDIPO 2021).

AI can also play an important role as part of a **predictive maintenance** system, e.g. in the safety management of hazardous plants. Improved defect detection based on prediction outcomes could help to avoid disastrous failures. In industrial production, machine learning applications, according to Çınar et al. (2020), provide several advantages, which include repair stop reduction, spare-part life increases, repair verification, and increase in overall profit. Specifically, the possibility to increase the remaining useful lifetime of industrial equipment might have notable positive environmental effects. However, the potential of predictive maintenance depends on the objectives and use context of the system: E.g., there can be conflicting objectives between reducing cost and reducing environmental impact (Carlson et al. 2020).

2.1.5. AI applications to strengthen environmental administration and participatory governance

AI is playing an increasing role in the development and application of regulatory technology – so-called 'RegTech', a concept which originated from the field of financial regulation. RegTech, according to Deatherage (2021), is simply the extrapolation of the ideas around automating compliance and providing insight. In general, all the functions of AI explained in Figure 1 above may be applied for the purpose of more effective and efficient environmental regulation (Deatherage 2021).

AI can play an important role in supporting the **implementation and enforcement of EU (environmental) law** both by aiding effective action and by automating administrative decisions (Couldry and Powell 2014). A specific area where AI applications have already been developed for compliance purposes is crop compliance. Crop compliance maps are generated to track the implementation of measures under the EU Common Agricultural Policy for Romania (Robles 2020). The

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[6]   FUDIPO, Future Directions of Production Planning and Optimized Energy – and Process Industries, is a project funded by the European Commission under the H2020 programme, SPIRE-02-2016 topic: "Plant-wide monitoring and control of data-intensive processes".

adoption of 'smart meters' for polluting enterprises can measure and report real-time emissions data and support the enforcement of emission limits (Amasheva 2019).

AI could further play a role in monitoring specific offences, where conventional methods of monitoring prove too laborious (Purdy 2010). As an example, a predictive AI software named Protection Assistant for Wildlife Security (PAWS) has been developed to combat poaching. It integrates machine learning and game theory to predict poachers' behaviour. PAWS then suggests patrol routes based on the poachers' behaviour model (Fang et al. 2017). In this context, other AI solutions have also been developed to detect listing of wildlife for sale on major e-commerce platforms (Rusch and Arora 2021).

In the finance sector, AI is already advertised as a tool for **fraud detection**. Emissions trading systems such as the EU ETS have risks related to fraud, e.g. the experienced VAT fraud, unauthorised access to accounts in the registry through phishing attacks, identity fraud and risks of money laundering. Any AI supported applications for fraud detection developed for the finance sector could therefore also benefit complex emission trading systems. The detection of **fraudulent ecolabels and product declarations** may also be improved with AI. Such use would require that third party certified environmental labelling programmes start using AI in their procedures for tracking labelled products.

Digital modelling of policy options can help in making **more effective governmental decisions**, such as in the context of urban governance and planning. As an example, Imec and the Netherlands Organization for Applied Scientific Research (TNO) launched the 'digital twin' of the city of Antwerp in 2018. The digital 3D replica of the city combines noise pollution data with real-time sensor information from air quality and traffic, as well as computer models. Its aim is to provide an up-to-date and predictive view of the city in which the impact of planned government measures can be simulated and tested (Imec 2018). As another example for potential of AI in urban governance, sensors with integrated AI systems are being used to anonymously identify different types of road users at selected junctions and control traffic signals to allow different modes of transportation to be prioritised as and when required. With more cyclists on the road as people avoid public transport due to COVID-19, these 'smart junctions' will be able to give priority to people on foot or bike where and when appropriate (Vivacity Labs 2020). AI could provide a variety of solutions to urban planning and governance problems, like the search for optimal future land use and transportation (Wu and Silva 2010; Wang et al 2020).

Finally, AI applications could offer new potential to better involve citizens in planning decisions. For example, the IBM technology 'project debater' will be able to meaningfully engage in a live debate with a human, absorb massive and diverse sets of information and perspectives and help people build persuasive arguments and make well-informed decisions. The technology is supposed to help in dealing with polls or surveys by sorting out complex and controversial issues, supporting the weighing of different positions and thus enabling well-informed decision-making (Curioni 2019). Municipalities wanting to create more green spaces could for example ask their citizens to participate in a survey in everyday language. AI systems could synthesise millions of responses and identify the most important points of view and their weighting (Schmidt 2021). AI-supported qualitative text analysis tools (e.g. NVivo or ATLAS.ti) are regularly used to structure and summarise contributions in public consultation processes with a large number of stakeholders (e.g. AI was used in processing the more than 16,000 submissions received in the EU's public consultation process on its common agriculture policy). Given the paramount importance of participation, acceptance and policy communication, especially for green transformation approaches, such applications could play an important role in the context of the EGD.

2.2. Potential of AI to help reach carbon neutrality and reduce energy consumption and negative impacts of human activities: sector-specific applications

2.2.1. Overarching trends

AI already plays a significant role in the context of the EGD. Surveys related to the current and planned use of AI technologies in the EU indicate that sectors with key relevance for the EGD figure prominently among those that already use at least one or two AI technologies or plan to use AI technologies (see Figure 2).

Figure 2: Sectoral adoption of AI technologies

Sector (Part I)	At least one AI technology	At least two AI technologies	Plans to use
Agriculture, forestry and/or fishing	39%	24%	18%
Manufacturing	47%	27%	16%
Construction	36%	23%	16%
Oil and gas	38%	19%	6%
Waste management	31%	21%	27%
Water and electricity supply	45%	28%	17%
Trade, retail	38%	22%	20%
Transport	36%	22%	20%
Food	36%	26%	20%

Source: European Commission 2020.

PwC and Microsoft quantified the impact of AI on global GHG emissions and found it to potentially contribute a reduction of 1.5 – 4% in 2030 or 0.9 – 2.4 Gt CO_2e relative to a Business as Usual (BAU) scenario (Gilham 2020). However, no details are provided regarding this scenario, apart from the fact that it being a mix of three different BAU scenarios by different organisations. It is stated that some or all of the AI effects considered could already be part of the baseline assumptions on carbon intensity changes. This means that there could be lower or even no additional effects relative to the BAU scenario which already assumes efficiency and optimisation improvements. The paper generally lacks transparency regarding its methods, assumptions and the specific AI applications considered. It is therefore not possible to confirm the estimates provided. The effects quantified as AI effects are often very indirect effects of AI, e.g. it is assumed that AI leads to a considerable price decrease in renewable energies, which has a strong mitigating impact. However, this price reduction for renewable energies is already a clear trend without AI and should not be accounted as an AI impact. The Boston Consulting Group (BCG) published an even higher estimate of a GHG emission reduction between 2.6 and 5.3 Gt CO_2e in 2030 but did not provide any methodologies or assumptions on how this estimate was produced (Degot et al. 2021). In addition, the estimate was published in an advertising context for the company and may not withstand scientific scrutiny.

2.2.2. AI solutions in the energy sector, in particular in the buildings sector

a. AI solutions in the buildings sector

AI is receiving increasing attention for supporting the reduction of greenhouse gas emissions in the buildings sector, where the various applications can be classified in two main categories: 1) **applications addressing energy consumption and greenhouse gas emissions in the use phase** of the building, and 2) **applications addressing the construction phase** of the building.

Both categories address key priorities of the different initiatives under the EGD: With the buildings sector being responsible for about 40% of energy consumption and about 36% of CO_2 emissions in the EU (European Commission 2020e), addressing the energy use of buildings is a key priority in order to meet the EU targets for greenhouse gas emissions as well as the targets set under the Energy Efficiency Directive. Furthermore, the Renovation Wave Communication sets the target of doubling the renovation rate and promotes life cycle thinking and circularity, where applications of AI in the construction sector may provide new opportunities.

Within the first category, AI can contribute to energy saving by facilitating energy profiling and demand estimation as well as assisting in appliance profiling and fault detection (Djenouri et al. 2019). Several contributions have confirmed that it is possible to utilise AI for detecting anomalous energy consumption behaviours either generated by end users, appliance failures, or other causes (Himeur et al. 2021). While artificial neural networks have been broadly utilised for building energy estimation and are the most commonly used technique in this area (Seyedzadeh et al. 2018), the application of AI in monitoring and optimising energy consumption in buildings also includes other techniques such as the Classification and Regression Tree (CART), the Support Vector Machine (SVM), the Linear Regression (LR), the autoregressive integrated moving average (ARIMA), and the seasonal autoregressive integrated moving average (SARIMA) methods (Chou and Tran 2018).

Within the second category, AI has the potential to increase productivity in the construction sector (Darko et al. 2020), support resource efficiency and the reduction of waste in construction (Ali et al. 2019) and increase energy efficiency (Kim et al. 2011; Mehmood et al. 2019).

Given the considerable efforts needed to meet the objective of doubling the renovation rate outlined in the Renovation Wave Communication, particularly in view of the labour shortage that is currently observed in the retrofit market (Kenkmann and Braungardt 2018), AI technologies have the potential to contribute to meeting the challenge. Furthermore, AI may contribute to reducing life-cycle emissions in the buildings sector. However, while AI is playing an increasing role in the architecture, engineering and construction industries, its application to energy and resource consumption is currently still limited (Darko et al. 2020).

b. AI solutions in the energy sector

i. *Flexible integration of renewable energies in future energy systems*

Decarbonisation will require switching to renewable electricity production. This will lead to considerably more decentralised electricity producers, supply influenced by weather conditions and daytime with the need for flexible generation and storage solutions. Intelligent power grids (smart grids) combine generation, storage and consumption. A central control system using AI optimally coordinates between generation, storage and consumption and thus balances out power fluctuations – especially those caused by fluctuating renewable energies in the grid. AI is already used to **control grid networks, forecast supply and demand, and optimise load management** and is thus indispensable in the future to achieve efficient use and integration of high shares of renewable

energies. For example, the company Veritone Energy provides customisable AI solutions to energy utilities drawing on weather forecast, energy demand, pricing and grid device data to automate the forecasting processes in real time (Veritone 2021). Siemens (2020) has included AI in its portfolio of applications that build, operate and maintain smart grids and a large number of start-ups have started developing AI solutions for smart grids.

ii. *Optimising renewable energies*

As in other sectors, AI technologies can **further optimise renewable energy production**. Reinforcement learning has for example been used to maximise electricity production from movable solar panels (Abel et al. 2018) or from wind turbines. It can determine optimal placement of turbines in wind farms (Dilkina et al. 2015). Machine condition monitoring systems are further being applied to wind turbines, in particular in remote areas and offshore sites for fault detection, automatic fault identification and prognosis of failure which enhances availability, production and reduces maintenance costs of wind farms (Hastings 2020). Other AI applications are able to detect faults in rooftop solar panels.

iii. *Methane leakage*

AI can also help to **predict methane leakage from gas pipelines and compressor stations, detect leaks and proactively suggest pipeline management**. The company Bluefield provides independent data using AI techniques and data from 23 satellites and provides CH_4 emission data for 120,000 companies in 130 countries and helped to identify the origin of methane leaks in different sites in Florida (Bluefield 2021).

2.2.3. AI solutions in the transport sector

a. Improved planning of transport systems and infrastructure

AI applications can improve the data available for the planning of transport systems and infrastructure. The gathering of such data can be improved through AI in combination with satellite data for vehicles (Kaack et al. 2019) and with automated analysis from cameras for pedestrians, cyclists or passengers in public transport. Smart card data in public transport and mobile phone data also provide large amounts of data, which can be used in combination with **AI for a better understanding of behaviour of transport users or mobility patterns**. Better data will allow improved modelling of transport demand in the short and long term and a **better planning of infrastructures and services**. Improved planning can reduce unnecessary travel distances, optimise vehicle routing, advance the combination of different transport modes, and optimise occupancy and loads. However, untapping this potential requires that planning authorities have access to AI-supported planning tools and the necessary data, and that transport is planned in an integrated way.

b. Improving energy and resource efficiency

Energy consumption of vehicles depends on many factors such as engine efficiency, aerodynamics, vehicle weight and tire resistance. AI can help in **optimising the design of energy-efficient vehicles** by improving the aerodynamics, power management or enhancing engines or reducing resource consumption. AI in this respect is not developing entirely new designs, but it can help improving existing designs based on criteria such as energy efficiency or resource use. Large brands such as BMW or General Motors are already using AI in car design (BMW 2021, Griffin 2021). GreenSteam is a company that provides software solutions for the marine industry to help reduce fuel use (Wolodozko 2021).

c. Modal shift to lower-carbon options

To increase the usage of sustainable transport modes with lower carbon emissions, it is necessary to understand transport mode choices. AI systems can be applied to **improve mode choice modelling by analysing data of passenger and freight transport** (Uddin 2021). AI systems **can improve the coordination of different transport modes** with predictive models. Low-carbon transportation options can be made more attractive to users through prediction of arrival times with automatic vehicle location systems (Jabamony & Shanmugavel 2020).

d. Electrification of transport

Electric vehicles are essential for decarbonising transport, provided that countries shift to renewable energies for electricity production. Research and development of efficient batteries integrate AI analysis of operational data. AI systems can **improve battery and charging management** (Rolnick et al. 2019). AI can also optimise charging of vehicles in times of high electricity supply and allow using car batteries as energy storage option for the grid. Machine learning has also been found more powerful than other methods to improve real-time power management in hybrid vehicles (Ali and Söffker 2018).

e. Operation of transport systems and traffic guidance systems

For freight transport, **freight consolidation (bundling of shipments) can reduce the number of trips and improved routing can avoid trucks with empty loads**. Shipment consolidation also enables the use of railways and waterways because these transport modes require larger loads than trucks. For logistics service providers, AI offers **opportunities to optimise the complex interactions of shipment sizes, destinations and transport modes and improve supply chain efficiency**. Deutsche Post DHL group has for example developed real-time routing algorithms for its fleet operation and drivers (Gesing et al. 2018).

In the EU, a key step towards the introduction of AI solutions in rail transport is the deployment of the **European rail traffic management system (ERTMS),** which provides trains with a driver assistance system. The ERTMS aims to harmonise EU rail transport systems by deploying **a single control, command, signalling and communication standard**. The ERTMS will reduce rail energy consumption, increase punctuality and line capacity and ensure technical compatibility between national rail systems. This can contribute to a more attractive European train network for long distances, which has the potential to replace flights and their associated much higher emissions. AI systems are also used to improve the performance and competitiveness of rail freight. The EU Shift2rail initiative is carrying out activities to better synchronise container train movements on the network, improve real-time information and data exchange (Shift2Rail 2021).

In aviation, **AI-based modelling of demand can improve operational efficiency to predict runway demand and taxiing time** to reduce excessive fuel consumption through airport congestion. Such a tool for efficient runway scheduling (Spot and Runway Departure Advisor SARDA) has been developed in a cooperation between NASA and American Airlines which has been optimised with machine learning techniques (Lee et al. 2015).

AI systems also help to keep the traffic flowing via traffic signals, and traffic lights that rotate in real time to meet on-the-ground traffic flow demands and an improved flow will reduce emissions.

f. Shared mobility

In recent years, the options for app-based ride services, ride pooling and different forms of car sharing have increased considerably. **AI plays an integral part in the optimisation of such mobility services**.

AI systems are used for efficient route planning, prediction of travel times, improvement of pick-up point selection, optimisation of fleets (Tiiku 2021) or scheduling of maintenance (Ilichev 2018). However, **the overall environmental impact of ride pooling is uncertain**. Data from a large survey in eight big cities and California in the US showed that app-based ride services mostly competed with environmentally-friendly transport modes and 60% of users would have otherwise taken public transport, walked, biked or would not have made the trip (Schaller Consulting 2018). The same source reports that, on average, the ride pooling in these US cities added 160% of vehicle miles due to rides without passengers before pick-up and after drop-off, longer routes for pooled services, or small rates of pooling achieved. The environmental impacts look better for station-based car sharing options. Results from the Netherlands showed that car sharers own 30% less cars than prior to car sharing, that they drive 15%-20% fewer vehicle kilometres and emit 13-18% less emissions compared to car use with owned cars (Nijland & van Meerkerk 2017). Reductions in car ownership, mileage and emissions are also confirmed by several studies in Germany (Loose 2016) and the UK (Steer Davis Gleave 2017). However, free-floating car sharing did not reduce emissions in a study in several cities in Germany, not even with electric cars (Hülsmann et al. 2018).

g. Automated vehicles and logistics

Around the globe, automotive manufacturers and technology firms are working on AI technologies to develop automated vehicles for road transport and fully automated vehicles are already being tested. **Automated driving could improve driving efficiency by 10-20%** (Wadud et al. 2016). **At the same time, the sensory technology entails an additional energy demand** which according to Mohan et al. (2020) will lead to a reduced range of electric vehicles of 10-15% for city driving. Each fully automated car will be generating around 4000 GB per day (Miller 2017). 1.7 million autonomous cars (0.2% of global car fleet) would generate the same data volume as the present global internet traffic (Liu et al. 2019). The network technology and the data processing infrastructure behind these data volumes will require large amounts of electricity and produce life-cycle emissions. Specific estimates are currently not available and will depend on the way the electricity will be produced.

In addition, **automated cars may offer new on-demand services which are likely to increase vehicle mileage because they will lead to additional empty trips for pick-up and drop-down compared to personal driving**. Automated cars may also induce transport demand from currently underserved groups (e.g. elderly and driving-restricted groups). Additional vehicle mileage will be linked with higher emissions. Whether automated driving reduces congestion may depend on the time perspective. In the short term, e.g. after an accident, it is likely that congestion dissolves more quickly, while in the long term congestion will depend on the physical limits of the road infrastructure (which cannot be changed by automation) and the number of vehicles. The long-term impact of fully automated vehicles on greenhouse gas emissions will depend on many factors such as the regulatory framework, but it is not unlikely that emissions will increase given the considerations above. Wadud et al. (2016) found many potential energy reduction benefits through partial automation, but also major energy/emission risks at full automation. Autonomous truck platooning – virtually linked trucks that travel in tandem with small intervehicle distances - in freight transport showed promising results and reduced energy consumption up to 10% due to lower air resistance (Zhang et al. 2020).

2.2.4. AI solutions in the agricultural sector

AI applications in the agricultural sector mainly **focus on intensive and industrialised farming systems**. The required data for these applications is generated through remote sensing technologies using satellites, planes and unmanned aerial vehicles (drones) and through on the ground sensors in combination with IoT technology. Especially the use of unmanned aerial vehicles has allowed scaling

up information collection, allowing the **development of applications ranging from the identification of water stress, monitoring of crop diseases and weed mapping to crop yield prediction** (Jung et al. 2020). AI techniques currently used in agricultural applications mainly fall under the machine learning category and include artificial neural networks (deep learning, e.g. convolutional neural networks) and decision tree algorithms (Jung et al. 2020). AI also underwrites the development of robotic applications in agriculture, for example for weeding and harvest.

a. Potential reduction of chemical inputs and improved nutrient management

The most advanced use case of AI in the agricultural sector is **precision agriculture, where AI enabled processing of data allows farmers to make temporally and spatially tailored management decisions, leading to a more efficient use of agricultural inputs, such as fertilisers and pesticides** (Finger et al. 2019). For example, agricultural machines equipped with cameras can generate images of plants in the field and deep learning-based image processing then allows for real time recognition of weeds, followed by the precise application of herbicides by the machine. This application is being developed in response to herbicide resistant weeds and is expected to reduce herbicide use by 77% per application (Blue River Technology 2021).

Machine learning is also enabling **analysis of bacterial and fungal soil diversity in combination with soil chemistry data.** This allows for a faster analysis of the impact of different management practices, potentially giving farmers the choice between pesticides and management alternatives such as planting of cover crops (Trace Genomics 2021). Another example is the **use of image recognition for pest identification to prevent infestations** and implement integrated pest management (Plantix 2021b). Plantix offers real time management advice to farmers who send images of their crops via WhatsApp and receive responses from a chatbot (Plantix 2021a). This can improve early on detection of infestations and is also an example of how **AI, in this case natural language processing, can support and improve farm advisory services**.

AI analysis of hyperspectral imagery of plants in the field allows to **identify nitrogen and phosphorus deficiencies to inform fertiliser application** (Cloud Agronomics 2021) **and optimise soil nutrient flows**. Nutrient deficiencies in plants can also be identified through photos and image recognition (Plantix 2021a). These techniques provide information to farmers more quickly than the traditional field sampling and laboratory analysis (Feng et al. 2020).

Finger et al. (2019) conducted a literature review collecting a range of case studies that show potential positive impacts of precision agriculture. For example, for **fuel consumption by agricultural machines, literature shows a reduction between 6% and 25%. Values for reduction in pesticide application (herbicides and insecticides) range from 11% to 90% (average 25%).** For N_2O emissions, they identified an **example where nitrogen application at variable rates reduced emissions by 34%**, and another example where an increased but variable nitrogen application did not result in increased emissions. However, Finger et al. also stress the **high uncertainty around the magnitude of positive effects and that figures known so far are case specific**, i.e. they depend on the analysed crop and surrounding environmental conditions.

b. Potential reduction of water consumption

AI is also used to determine soil moisture and other relevant parameters that can guide farmers in making **more efficient use of irrigation water**. This is achieved through combining satellite imagery and information on precipitation volumes (HelioPas AI 2021). Optimising irrigation also depends on accurate weather information, given that weather directly influences evapotranspiration. Thus, **AI applications to improve weather forecasting, even to the farm level,** have recently increased (i.e.

Roach 2019, Fasal 2021). Considering the potential impacts of climate change-induced climate variability, this use of **AI could support farmers in climate change adaptation** (see section 2.2.5).

c. Potential contribution to climate change mitigation

Agriculture is responsible for 10% of the EU's GHG emissions (436 Mt CO_2eq). CH_4 from enteric fermentation of sheep and cattle makes up 42% of agricultural emissions and N_2O emissions from agricultural soils and manure management make up 43% (EEA 2020). Precision agriculture can directly reduce fuel consumption from agricultural machines and could potentially have positive second order effects for energy use. For example, a more efficient use of inputs could reduce the energy consumption required for their production (Böcker et al. 2019). Also, if AI leads to a decrease in anthropogenic nitrogen inputs (from mineral or organic fertilizers) into cropland and grassland, it could help reduce direct and indirect N_2O emissions from agricultural soils and nutrient runoff into water. Currently, N_2O emissions make up around 3.9% of total net EU GHG emissions in 2018 (EEA 2020)[7]. A commonly reported effect of new technologies in agriculture is the increase of yields (Lezoche et al. 2020) and the potential to preserve soil health. If this leads to less pressure for expanding agricultural area or frees up crop- and grassland on organic soils, it could have a positive effect on emissions from land use. In 2018, 30 Mt of CO_2 emissions from the EU originated from organic soils (Böttcher et al. 2021). However, this is an uncertain effect since many other factors contribute to farmer's land management decisions.

A more direct contribution to climate change mitigation could arise if AI is effectively leveraged to improve carbon content of agricultural soils. Cloud Agronomics is using hyperspectral measurements of soil and deep learning to better quantify soil carbon (Cloud Agronomics 2021). This technology could decrease costs of monitoring soils, at least the upper layer, and analysing whether measures to increase soil carbon content are effective.

d. Limits to AI in agriculture

Currently the main focus of AI applications in agriculture is not on addressing environmental concerns, but in increasing productivity and addressing labour shortages (Lakshmi & Corbett 2020). Thus, there is a general lack of data on the environmental impacts of the technology, especially considering the diversity of farming systems. Given that current developments are focused on widely grown crops (e.g. wheat, maize and rice) in industrialised farming settings, **wide adoption may lead to unsustainable intensification** (Walter et al. 2017), perpetuating current "blind-spots of western technologies" with regards to different food cultures and food systems (FAO 2020). Most analyses showing efficiency improvements focus on the individual farm level and there is a **knowledge gap regarding potential rebound effects that lead to higher overall inputs across the agricultural system** (Paul et al. 2019).

2.2.5. AI solutions in other areas addressed by the European Green Deal (circular economy, pollution, biodiversity, adaptation to climate change)

a. Circular economy

There are several opportunities for AI to strengthen a circular economy (Ellen MacArthur Foundation (2019):

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[7] The EU GHG inventory for 2018 includes the UK and Iceland.

AI can **support designers in accelerating the design of products, components and materials** with longer lifetimes, improved recycling capacities, less toxic substances and lower emissions. An AI system can suggest initial designs or adjust designs based on environmental parameters. This makes eco-design more effective and deals with the complexity of materials. AI in design requires well labelled and complete data bases on materials and their technical and environmental impacts. An example of a use case for AI in design is the project 'Accelerated Metallurgy' funded by ESA which developed novel metal alloy combinations taking into account circular economy principles such as non-toxicity, design for use and re-use, extending the use period and minimising waste. AI techniques were used to map new alloys in structure, process and properties based on the chemical, physical and mechanical properties and select promising metal alloys taking into account life cycle emissions (European Commission 2017).

At the end of the product lifetime AI systems can **assist the inspection, sorting, separation and disassembling process to circulate materials in the economy** using the AI function of classification and pattern recognition to identify objects or materials. For example, the company ZenRobotics uses AI-powered robots to analyse waste streams and to separate waste fractions with high precision for different kinds of waste: commercial and industrial waste, municipal solid waste, plastic, packaging, scrap metal or construction and demolition waste (ZenRobotics 2021). Companies such as Reconext offer aftermarket device services and reverse supply chain solutions for electronic devices (Recontext 2021). They use AI to assess the condition of electronic devices and determine if they can be reused, repaired, refurbished or recycled.

AI can also **increase the effectiveness of circular economy business models**. Matching algorithms can connect users on second-hand platforms with the required product. AI supported predictive maintenance can steer demand for repairs and extend lifetimes of products.

The potential value unlocked by AI in the circular economy for consumer electronics was estimated by the Ellen MacArthur Foundation (2019) at US$ 90 billion per year in 2030 through the extension of use periods (US$ 50 billion), e-waste recovery (US$ 24 billion), increased material efficiency (US$ 8 billion) and optimisation and acceleration of innovation processes (US$ 8 billion).

The **largest potential for transformational changes is likely to come from a design without waste**. However, whether the enhanced environmental design options presented by AI technologies will really be used in practice will depend on the regulatory framework and whether there are sufficient incentives from environment legislation to pursue these options. E.g. in the example presented above on 'Accelerated Metallurgy', product designers can either use the generated information to choose the cheapest alloy options for a specific product or to choose an economic or environmentally optimal option. This example also shows that the reduction of the environmental impacts depends on the quality of the environmental information available. If 90% of potential metal alloys have never been tested, there may be unknown detrimental environmental effects and the AI suggested alternative alloys may still cause new environmental problems.

b. Pollution

AI-based solutions can help **simulate, predict, measure as well as monitor pollutant dispersal**. In addition, it can serve to **optimise and control pollutant removal** from the environment. Such applications can be found in the field of air, soil and water pollution, including marine pollution as well as pollution control in relation to wastewater and solid waste.

For example, with regards to clean air, AI applications can provide predictions and/or forecasts of pollution levels several days ahead. In consequence, they can also provide for air quality alerts. Also, as

they allow for real-time pollution monitoring and air-pollutant source detection, they can help in the monitoring and prevention of air pollution (Liu et al. 2019).

One such application, Hawa Dawa, specialises in the measurement and analysis of airborne contaminants for a wide range of purposes, such as city planning or health and traffic management. It integrates data from multiple sources such as satellites and public measurement stations, as well as the company's own air quality nodes. Different from public data collection stations, the air does not require extensive treatment prior to analysis. Instead, Hawa Dawa uses AI-based calibration algorithms to take into account cross-sensitivity of the pollutants and exclude environmental factors, such as temperature, relative humidity or air pressure from the data. Further data layers, e.g. weather or traffic date, can also be integrated into the analysis[8].

In the field of water pollution, researchers in the UK used machine learning to identify unreported and untreated sewage spills from two wastewater treatment plants. The computer algorithm was trained to recognise, through daily effluent flow patterns and operator-reported incidents of untreated sewage discharges, i.e. known spill events, when a spill was likely happening. The algorithm reportedly detected close to a thousand previously unreported spills over the course of eleven years (Hammond et al. 2021).

c. Adaptation to climate change

For adaptation to climate change it is important to have **information on expected climate change and its precise and regional impacts.** Machine learning techniques have been explored to be integrated in the climate modelling work. These techniques may be more accurate or less expensive where existing models are too computationally expensive or where large amounts of data are available, but difficult to model in systems with traditional physical-chemical properties and statistics (Kochanski 2020). Gentine et al. (2018) trained a deep neural network on a high-resolution model to better represent convection and showed that such an approach was much faster and computationally more efficient: Thus for some model components, AI can be used to accelerate the models and decrease costs which will benefit the prediction of climate change and its impacts and can enhance granularity of regional prediction.

To **make climate impacts more realistic for more people**, researchers from Montreal Institute for Learning Algorithms (MILA) and ConscientAI Labs used generative adversarial networks, a machine learning technique, to simulate what homes are likely to look like after being damaged by rising sea levels and more intense storms. Such applications could increase awareness for the need of adaptation actions (Snow 2019).

d. Biodiversity and nature conservation

In the field of biodiversity and conservation AI-based solutions offer a wide range of opportunities. They can help in the **planning of conservation habitats**, e.g. by monitoring ecosystems, detecting and monitoring habitat loss, simulating animal and habitat interactions or by predicting animal migration patterns. For instance, the Group on Earth Observations Biodiversity Observation Network (GEO BON) uses remotely sensed and in-situ data to support the monitoring of biodiversity and ecosystem service changes, aiming to provide high quality observations, information and data to scientists, decision-makers and the public. One of GEO BON's products are global change detection maps of forest cover[9].

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[8] Additional information can be found on the Hawa Dawa webpage available at: https://hawadawa.com/.

[9] Additional information on the GEO BON products can be found on the GEO BON webpage available at: https://geobon.org/.

In relation to **species control**, AI systems can be used to survey threatened, invasive or dangerous species and obtain accurate population and location estimates. They can also monitor the health of certain species. Current commonly used monitoring techniques, such as camera traps and surveys performed on foot, are known to be very resource intensive and potentially inaccurate and imprecise. AI, in combination with other technologies, such as unmanned aerial vehicles or miniaturised thermal imaging systems, represent a new opportunity to survey larger areas more easily (World Economic Forum 2018). Projects like "Whaletrack" use satellite tagging to deliver insights into the migratory behaviour of whales. Acoustic sensor data can be analysed and evaluated using machine learning to identify different species in a field and study their behaviour (Liu et al. 2019).

As already mentioned in section 2.1.5 AI can also help in **fighting illegal wildlife trade and foster sustainable trade**, e.g. by tracking high-risk animals, detecting illegal activities via imaging, predicting poacher routes or optimising patrol schedules, thus allowing authorities to more effectively intervene (Fang et al. 2017). In terms of sustainable trade, AI-based solutions can be used to optimise food value chains and supply chain monitoring.

AI-based solutions can moreover be used to **assess natural capital**, e.g. through registering biological and biomimetic assets and supporting plant species identification (World Economic Forum 2018) For example, the Earth Bank of Codes aims to create a library of the genomic codes of all known species, accessible to scientists and businesses around the world who seek to develop bio-based innovations. Its idea is to tap into the wealth of nature while tackling bio-piracy and ensuring fair and equitable sharing of the commercial benefits. AI techniques used will include natural language processing, deep learning, computer vision, probabilistic programming and an array of statistical machine-learning techniques [10].

2.3. State of play and research trends to mitigate the adverse consequences of AI

The assessment of the environmental impacts of digital technologies is complex: The application of AI requires the use and expansion of digital hardware and infrastructures (such as data centres and networks), which leads directly to an increasing consumption of electricity and related materials and resources.

The differentiation of first order, second order and tertiary or systemic effects (see section 1.3) is of specific relevance with respect to approaches and instruments to mitigate adverse environmental impacts of AI: It can make a big difference for such instruments and approaches whether e.g. the production, use and disposal of ICT hardware or software is regulated on the basis of clear standards and targets, or whether the cumulative and indirect effects of the reactions of consumers or companies to new technologies are taken into account. We therefore start with discussing first and second order environmental effects (2.3.1.) followed by systemic environmental effects (2.3.2.).

2.3.1. State of play and research trends in mitigation options to address energy consumption and resource use and waste generation

a. Energy consumption

AI requires ICT hardware to be programmed, trained and deployed in its productive application phase. The operation of digital ICT infrastructures and end-devices is a major contributor to overall electricity consumption. It is currently not possible to determine the proportion of energy consumption caused

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[10] Additional information on the Earth Bank of Codes can be found on the website available at: https://www.earthbankofcodes.org/.

by the operation of AI in digital hardware, data centres and networks. Although the application of AI is steadily increasing, to date most ICT hardware is likely to be operated primarily by traditional algorithm-based software. The following figures therefore represent a gross overview of the estimated overall power consumption of ICT infrastructure. Most digital data processing today takes place in large data centres and digital networks, rather than in user end devices. It can be assumed that large data centres will also be the hotspot of AI application. This is true regardless of the fact that AI functions can also be implemented in user end devices on a micro level, e.g., in self-learning thermostats.

Digital infrastructures such as data transmission networks and data centres have continuously increased in size and capacity. A comprehensive assessment of the energy and resource consumption of the global digital infrastructures has not yet been undertaken due to the lack of a global ICT inventory. The International Energy Agency (IEA 2020) estimates that global internet traffic, one of the measurable indicators of digitisation, has grown 12-fold or about 30% per year since 2010. Looking forward, global internet traffic is expected to double to 4.2 trillion gigabytes by 2022. **Data centres, digital networks, and other ICT** consume about **7% of the world's electricity** today, and the share is projected to increase to 13% by 2030 (JRC, 2019). It has been estimated that ICT accounts for 5-9% of the world's total electricity use, which may rise to 20% in 2030 (Enerdata 2018).

The **electricity demand of data centres** in 2019 was around **200 TWh globally** (see Figure 3). This equals around **0.8% of global final electricity demand**. The energy demand of **data transmission networks** accounted for around **1% of global electricity use in 2019** (ibid).
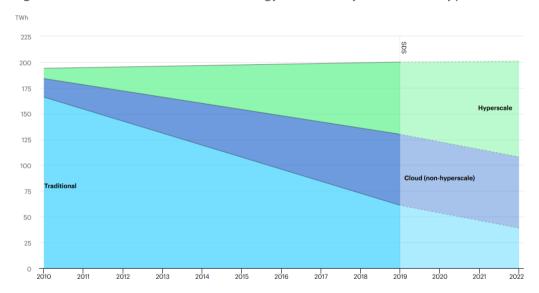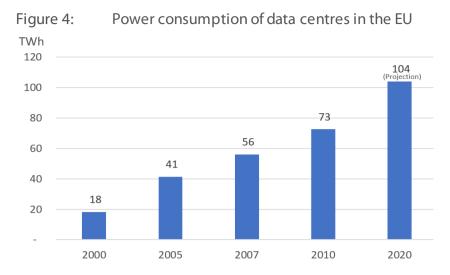
Figure 3: Global data centre energy demand by data centre type, 2010-2022

Source: IEA 2020.

The IEA (2021) notes that the total power consumption of data centres worldwide has not grown much since 2010 despite of a 7.5-fold increased computation workload and a 12-fold increased network traffic. Their future worldwide energy consumption is estimated to increase by 180% to 366 TWh in 2030 (best case estimate) (Andrae 2020a). In the EU, the energy consumption of data centres has continuously grown during the past two decades (Figure 4) (JRC, 2019).

Figure 4: Power consumption of data centres in the EU

Source: JRC 2019.

On the other hand, the energy efficiency of data centres has steadily improved over the last decade. This results mainly from the substitution of small data centres by 'hyperscale' data centres, which have better energy efficiency. Such large-scale data centres can be optimised for processor efficiency and idle power consumption reduction (Masanet, et al, 2020). Between 2016 and 2019, the global investment in hyperscale data centres more than doubled from €13 billion to over €29 billion in the fourth quarter of 2019. This trend is not expected to slow down anytime soon, with Amazon, Google, Microsoft, Facebook, and Apple spending the most on hyperscale investments.

Electricity consumption of data networks is estimated at around 250 TWh in 2019 (IEA 2020). A similar value has also been reported by the International Telecommunication Union (ITU) with 276 TWh in 2020. The absolute electricity consumption of networks is projected to rise to about 300 TWh in 2030 (ITU 2020b), although data transmission networks are rapidly becoming more efficient (IEA 2020). A further increase in the global energy consumption for their operation is expected because global data traffic is growing exponentially and therefore a continuous increase in infrastructure capacity is necessary. As a consequence, data centres and networks for processing and distributing the increasing amounts of data are becoming more and more environmentally impactful due to their immense power consumption (Liu et al, 2019).

Belkhir and Elmeligi (2018) estimate that the combined carbon footprint of **global data centres and communications networks** ranges from **1.1 to 1.3 Gt CO$_2$eq in 2020**. Andrae (2020b) estimates that the generation of electricity for **data centres** worldwide caused **greenhouse gas emissions** of approximately **0.16 ± 0.3 Gt CO$_2$eq in 2020**. A projection for 2030 indicates that the operation of data centres could contribute up to 0.42 ± 0.12 Gt to global CO$_2$ emissions. For **mobile network** use, the same author estimates **CO$_2$ emissions** in the range of **0.054±0.08 Gt CO$_2$eq in 2020** and 0.14±0.06 Gt CO$_2$eq in 2030. Emission estimates for **optical data networks** range from **0.083 ± 0.02 Gt CO$_2$eq in 2020** and they are expected to rise to 0.15±0.06 Gt CO$_2$eq in 2030 (ibid).

The **impact of AI on power consumption** of data centres and data transmission networks has not yet been assessed by publicly available studies. Possible significant paths of influence of AI on the energy efficiency of data centres result from a better utilisation of the existing infrastructure through intelligent load distribution and management of capacity reserves or back-up capacities. This includes the relocation and centralisation of computing capacity from end devices, such as personal computers, to data centres, which have better energy efficiency than most end devices. Hilty et al. (2015) have determined that "*software solutions for dynamic predictive load management in data centres promise*

energy saving potential of 25% to 30%". AI applications of that kind can help to make other computing systems even more energy efficient. This can be considered as a second-order effect. For example, energy savings have been observed when substituting personal computers (PCs) by thin clients for personal computers. Mehlhart et al (2016) extrapolated that the EU-wide replacement of 14 million PCs by 18 million thin clients results in potential savings of 4.5 billion MJ per annum in cumulated energy demand (CED) (as for 2020). This translates in a carbon footprint reduction of 0,4 Mt CO_2eq per year. It can also be assumed that machine learning might become a tool for more efficient scheduling of computing tasks and compression of data transmission between use end devices and data centres. AI could also help optimise software to become more resource efficient in terms of hardware utilisation. Algorithm-based software can influence the power consumption of computers significantly (Kern et al 2018).

On the other hand, AI is suspected of being itself an energy-intensive software application. García-Martín et al (2019) conclude from the analysis of training procedures in deep neural networks (DNN) that "*Machine learning algorithms consume significant amounts of energy*". Luccioni et al (2020) explain that the initial network training procedures requires enormous amounts of computing hardware time, which results in high power consumption and ultimately accounts for a large portion of CO_2 emissions. According to these authors, "*the computing power required for key machine learning tasks has doubled every 3 months or so, increasing 300,000 times between 2012 and 2018*" (ibid). They illustrate this with the common practice example of a state-of-the-art facial recognition model which's training "*with millions of parameters can take months on even the most powerful hardware*". Strubell et al (2019) estimated the energy-consumption related CO_2 emissions from the training of common DNN-based models for Natural Language Processing (NLP). They explain that nowadays, the training of advanced NLP models requires specialised hardware and the training process requires this hardware to run "*for weeks or months at a time*" (ibid). Their experimental study of the power consumption of a state-of-the-art NLP model during training and fine-tuning resulted in largely varying power consumption, depending on the respective combination of model architecture and hardware. In the case of neural architecture search for machine translation and language modelling, the power usage of the data centre (incl. cooling) was determined to be 656,347 kWh for a single run (ibid).

b. Consumption of material resources

Direct impacts on natural resources occur first in the production of microelectronic and ICT components, which form the basis for the operation of digital infrastructures required for the use of AI. In particular, the production of active semiconductor components is very energy and resource intensive. The **environmental and social impacts of extracting raw materials** for the manufacture of digital hardware are particularly evident in metals, such as **cobalt, palladium, tantalum, silver, gold, indium, copper, lithium and aluminium.** ICT hardware contains a multitude of materials, including many elements that are regarded as critical or that are mined only in small quantities. Digital end user devices such as smartphones and tablets are particularly resource consuming types of ICT because of 1) their relatively high content of critical raw materials, 2) the large number of devices in use, and 3) their rather short service life, which requires frequent replacement. Digital end user devices generate a significant demand for cobalt (~ 9.4% of global primary production) and palladium (~ 8.9% of global primary production). AI embedded in such short-lived end user devices, for instance in the form of tailored neural network, could lead to increasing demand for such materials, as the devices' increasing power consumption would necessitate the use of large batteries.

With regard to data centres, **resource** consumption is determined not only by their inventory of **ICT components** (e.g. servers, data storage), but also **by supporting systems** (cooling systems, uninterruptible power supply, buildings). The latter are usually much weightier than the server

equipment. They consist mainly of commoditised metals such as steel, aluminium and copper, as well as construction materials. The life of the support systems is usually measured in decades. In contrast, servers are made of typical ICT materials such as semiconductors, copper, precious metals and rare earths. Server ICT is replaced at intervals of a few years, up to a maximum of 10 years (depending on performance requirements). In terms of the depletion of natural resources, this means that the active ICT components in data centres are far more relevant than the supporting systems.

c. Approaches to analysing the direct environmental impacts of AI software

The German Environment Agency has published research showing that different **software** with the same functions, depending on how it is coded, **can cause different energy consumption** on the same hardware (Gröger et al. 2018). The research also served to develop a hierarchical catalogue of **criteria for sustainable software** (Hilty et al. 2017). The method proposes a set of criteria for assessing the environmental impact of software products. The criteria encompass, inter alia, energy efficiency, hardware efficiency (distinguishing local, network and cloud resources), hardware utilisation and sufficiency, software default settings and configurability, hardware resource management and obsolescence. On this basis, the same authors also outline a software tool for the recording and analysis of evaluation criteria for software (Gröger et al. 2018). The research results support the **development of a possible future "Blue Angel" eco label** for environmentally relevant software properties (ibid). While the evaluation method described above addresses algorithm-like software, assessing **AI will require further methodological developments**. This is because the architecture of AI may differ significantly from the current architecture of software and hardware. The techniques and approaches used and because it may even be accompanied by novel hardware design concepts (e.g. field-programmable gate arrays, in-memory processing, neuromorphic chips). The application context is also likely to change radically compared to traditional software when AI is used in autonomous systems with little to no human interaction during runtime, up to the extent that AI takes over the training of AI. Hence, the assessment of energy and resource consumption impacts needs to address the novel features of AI and its context of use. AI applications should also be optimised for their energy and hardware resource consumption during development and iteratively tested during the training phase to ensure that they are as energy efficient as possible. In addition, a monitoring system with suitable key performance indicators should be developed that documents the energy consumption of each AI application with verifiable information.

2.3.2. State of play and research trends regarding systemic adverse impacts and options to mitigate these risks

In addition to direct impacts of AI, systemic and – possibly – unintended environmental effects of AI systems have to be considered. To evaluate such effects, it is necessary to understand how AI changes production and consumption patterns, i.e. what goods and services people consume, how they are produced, and how the product systems interact with the environment (Bieser and Hilty 2018).

a. Causal factors of systemic effects of AI

An understanding of how systemic effects relate to the dynamics of AI-based decisions – i.e. on which level of the decision-making mechanisms of the respective AI systems' problematic steering objectives evolve – is highly relevant to determine the effective regulatory intervention to implement sustainability goals. Assessing and evaluating the real-world effects of AI systems constitutes a challenge. However, a range of environmental risks related to individual use contexts and user preferences and the economic and technological integration of systems have been described (Bieser and Hilty 2018).

It is important to note that systemic effects, such as overall impacts of increased consumption, are not at all necessarily unintended. Changes of consumer behaviour can be the primary objective or a welcome side effect of economic actors who want to increase their sales or market shares: e.g. digital shopping assistants are specifically designed to 'nudge' users to make purchases by means of preference-optimised offers and are very much intended to bring about a significant increase in consumption (Hanslik 2018). From a business perspective, the integration of AI to boost the environmental sustainability of purchases is made to appeal to new consumer segments (Frank 2021). A consequent increase in consumption could neutralise the environmental benefits of a more sustainable production.

The potential of AI for information gathering, optimisation and improved decision-making is not limited to environmentally friendly applications and can of course also be used for activities that cause environmental problems. Machine learning is currently widely used to increase oil and gas production (NETL 2020). The Norwegian University of Science and Technology (NTNU) launched the Centre for Integrated Operations in the Petroleum Industry, focused on developing novel and innovative methods based on AI for oil and gas production optimisation (Dale and Uglane 2018). As another example, the machine learning tools of tech giants are being commercialised to help oil and gas companies locate fields and maximise production, e.g. by creating more accurate 3D models of rock and fluid properties that reveal exactly where to drill (Koroteev and Tekic 2021). A recent Greenpeace report indicated that Amazon, Microsoft and Google have all established contracts to use AI to unlock oil and gas deposits with major oil and gas companies such as Shell, BP and others (Greenpeace 2020).

More generally, it is assumed that commercial actors tend to implement steering goals when designing AI systems which are incompatible with public welfare goals, and 'private sector' AI systems might be more prone to create negative externalities (Slee 2020). This assumption also supported by empirical studies in prominent fields of application for sustainable AI systems, for example in agriculture (Wuepper et al. 2020).

In many cases, adverse effects of AI systems are consequences of interactions of the AI systems' design and the adaptation of user or producer behaviour as a reaction to the new technologies. Adverse effects resulting from changed consumption patterns have prominently been identified for Video Streaming Services: Streaming movies and TV series on platforms such as Netflix is significantly more energy-efficient than using DVDs. Since flat rate offers are cheaper and access to movies on streaming services is less complicated, however, considerably more movies are watched overall, which erodes the efficiency advantage of streaming. More generally, as the efficiency of available computer systems increases due to better technologies, so do the demands on the energy and resource intensive capabilities of the operating system and software (Sühlmann-Faul and Rammler 2018). The overall negative environmental impacts related to the increasing use of self-driving cars as described in section 2.2.3.g. also illustrate how an interplay of user behaviour, intended design and the overall integration of AI systems in society may lead to adverse systemic effects.

Other prominent examples illustrate that adverse consequences of AI systems due to changed consumer behaviour can even run contrary to the intended pro-environmental functions of an application: e.g. products designed to automatically manage and implement more efficient energy consumption might have unintended consequences on consumption behaviour by inducing people to abdicate their control of energy consumption. This can ultimately result in excessive energy consumption (Puntiroli et al. 2019). Knowing that a product is sustainable is likely to actually increase consumption – for example using more water or energy in ecolodges (Font and McCabe 2017). This is also described for perceived environmental benefits based on AI systems to enhance the

environmental sustainability of products, which accordingly can drive a consumer's purchase intent (Frank 2021), even if this may not be the objective.

The structural problems behind the adverse and possibly unintended environmental effects caused by AI have not yet been systematically investigated. However, there are good arguments for looking at such problems under the aspect of **data input**. The rise of ethically problematic decisions due to qualitatively insufficient data input has been frequently described, e.g. when the data basis of AI decisions reflects previous discriminations, which then are perpetuated and reinforced by the decisions (EU Fundamental Rights Agency 2019). Comparable deficits and dynamics however also may be identified in many systems that develop their steering goals on the basis of feedback data on everyday habits or consumer preferences. These data may be qualitatively insufficient with regard to sustainability aspects in systems which can create negative external effects, as they neither represent values of nature nor the preferences of third parties or the common good (see Bonnefon et al. 2016). Systems that form their objectives based on pre-existing consumption preferences or patterns of behaviour thus could further reinforce unsustainable habits and practices. Regarding risks of discrimination, consideration should be given to how externalised (common) interests can be fed into the dynamics of AI decision-making.

Summarising, the questions of how systemic environmental effects can be avoided and how environmental goals can be integrated into algorithms must focus on the decision-making mechanisms of AI systems as a whole. The examples indicate that regulation may target **two general entry points to implement green goals** into AI systems: On the one hand, 'green' policies can focus on the developers or providers of algorithms. On the other hand, the goals of AI systems are not only integrated by design in line with the intention of the producers, but also develop automatically and dynamically based on data. Thus, regulation must specifically also take into account the data used to train AI.

b. Instruments to mitigate systemic effects

Awad et al. (2020) summarises three points, which may make it difficult for common regulatory approaches and policies to tackle negative externalities of AI. First, intelligent machines are often black boxes: it can be unclear how exactly they process their input to arrive at a decision, even to those who actually programmed them in the first place. Second, intelligent machines may be constantly learning and changing their perceptual capabilities or decision processes, outpacing human efforts at defining and regulating their negative externalities. Third, even when an intelligent machine is shown to have made biased decisions, it can be unclear whether the bias is due to its decision process or learned from the human behaviour it has been trained on or interacted with. Further research is needed on suitable instruments of environmental law and policy to deal with these obstacles.

Based on the above-mentioned entry points for environmental regulation, programmes, and initiatives, three types of approaches may be differentiated.

First, given the relevance of human decisions regarding the design of AI systems, regulation may focus on **empowering specific actors, incentivise sustainable applications and on improving their market opportunities**. Numerous approaches in this sense aim at promoting the implementation of sustainability goals by exerting influence on actor constellations or by improving the market conditions for sustainable AI. For example, the German Ministry for the Environment, Nature Conservation and Nuclear Safety sponsors specific AI flagship projects (BMU 2021). The market opportunities for sustainable innovations may also be strengthened by loans aligned with the future EU taxonomy or by targeted 'green' adjustments to public procurement law (Hedberg and Šipka 2020). With a view to

actors operating in the public interest, consideration can be given to how municipalities can become more active in fields of the digital economy to pursue municipal policy objectives (Ringwald et al. 2019).

Secondly, instruments of **precautionary environmental law** appear suitable, in principle, for addressing complex environmental impacts that are associated with systemic and possibly non-intended effects of AI. European environmental law stipulates metrics, targets and/or independent risk assessments, e.g. of manufacturers of hazardous products, and is intended precisely to better deal with indirect, cumulative risks and impacts that are difficult to predict, measure and attribute (Reese 2010). It is thus hardly surprising when scholars propose instruments such as binding **environmental impact assessments** to address systemic environmental effects of AI (Rejeski et al. 2018). It has been discussed how Environmental Impact Assessments provide a partial blueprint for the assessment of impacts of AI on human rights and interests (Calvo et.al., 2020). It should, however, be further analysed how the **assessment of environmental impacts of AI** can be integrated in the existing European regulatory framework and how existing approaches for the assessment of environmental impacts could be adapted to the reflect the specific characteristics of AI Research that generates empirical data and appropriate standards[11] is a prerequisite for developing appropriate regulatory instruments to assess the environmental impact of AI.

In principle, such legal approaches seem to be compatible with proposals for an **AI Regulation, such as the recently proposed EU Artificial Intelligence Act**[12]. The proposal for the regulation stipulates, on the one hand principle-based requirements that AI systems should comply with. On the other hand, it is centred on a risk-based regulatory approach. The Artificial Intelligence Act stipulates that 'high-risk' AI systems that pose significant risks to the health and safety or fundamental rights of persons will have to comply with a set of horizontal mandatory requirements for trustworthy AI and follow conformity assessment procedures before those systems can be placed on the Union market (European Commission 2021c). This risk-based approach is comparable to previous proposals which suggest providing for differentiated duties to control and correct algorithms, depending on the severity and probability of harm. (Datenethikkommission 2019, Zweig 2019).

Approaches to assess and control the environmental risks of AI ex ante are plausible, in particular, for key technologies such as autonomous driving and should be further investigated. It should be acknowledged, however, that environmental risks do not play a significant role in the proposals or ongoing standardisation efforts to date. The proposal for an EU Artificial Intelligence Act refers to environmental sustainability with respect to potential infringements of the right to a high level of environmental protection and the improvement of the quality of the environment (Article 37 of the EU Charter of Fundamental Rights) including in relation to the health and safety of people. Environmental sustainability can also be included in the proposed framework for creating voluntary codes of conduct (Title IX). At least where human rights or clearly defined human interests are not simultaneously concerned, environmental risks remain outside of the scope of the binding norms of the proposal. More generally, the difficulties to assess and allocate risks triggered by AI, which may lead to environmental impacts as a result of several interacting causes and potentially in the long term, could pose an obstacle to a risk-based approach to regulation. There is still a need for research on how and to what extent precautionary, risk-based regulation of algorithms can contribute to an effective regulation of complex, dispersed or cumulative environmental hazards.

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[11]   See above, section 2.3.1.c.

[12]   Proposal for a Regulation of the European Parliament and of the Council Laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act), COM (2021) 206 final, 21.4.2021.

Data regulation and data governance should be considered as a **third general approach** to regulating AI. This already follows from the overarching relevance of training data and feedback data for the production and operation of AI systems. From an environmental policy perspective, it appears essential to ensure sufficient access to data for sustainable applications and regulators. Data also plays a significant role for other policy instruments: E.g., in isolation from adequate data governance, funding mechanisms, which support sustainable AI applications or aim at empowering public interest actors may have little chance of success. Strong legal or technical barriers to using relevant data, whether held publicly or privately, can hinder both meaningful innovation and appropriate regulation of and by AI. Access to the data, used to train AI systems, is also necessary for a risk-adapted AI regulation. The problem of complex and dynamic decision-making systems is tackled by analysing the processed data.

Data not only conditions and enables other regulatory approaches. It is also increasingly understood that the way in which access to data is organised – i.e. how data is shared and how authority and control over data is allocated – is fundamental for the outcomes of AI decisions (Janssen et al. 2020). Data governance and data regulations thus could help to ensure that relevant AI systems make their decisions in accordance with principles of an ecological common good. Recent proposals and debates about alternative, democratic data governance or representative data rights (Hummel et al. 2020, Vilijoen 2020; Fezer 2018) indicate towards legal and organisational pathways to integrate data into the decision-making mechanisms of AI systems, which may reflect sustainability principles better than systems which rely on data on consumer preferences or habits.

Enabling citizens to actively decide, who can use their data and for what purposes, combined with trustworthy technologies, processes and actors, can also create incentives to share or generate such data. In this context, for example, the creation of registered "data altruism organisations" under the recently proposed European Data Governance Regulation (European Commission 2020f) is intended to help ensure a higher level of trust in data provision and thus contribute to more data being made available by data subjects and companies in order to achieve higher levels of development and research.

3. EU PROGRAMMES AND INTERNATIONAL COOPERATION

3.1. EU programmes and policies

In addition to the recent proposal of a European AI Act, briefly described above, a number of other EU programmes and policies have to be mentioned. A digital transformation which contributes to a sustainable, climate-neutral and resource-efficient economy is a key objective of the Commission's **digital strategy** and its **White Paper on Artificial Intelligence** (European Commission 2020a, 2020b). Both understand AI as a critical enabler for attaining the goals of the EGD. The White Paper on AI focuses on the legal and ethical framework necessary to create an 'ecosystem of trust' for AI and outlines how the Commission will support and promote the development and uptake of trustworthy and human-centred AI in the EU.

The **European Data Strategy** is part of the coordinated plan on AI and provides specific linkages to environmental challenges and the sectors covered by the EGD. The data strategy aims to create "*a single European data space where personal as well as non-personal data, including sensitive business data, are secure and businesses also have easy access to an almost infinite amount of high-quality industrial data, boosting growth and creating value, while minimising the human carbon and environmental footprint*" (European Commission 2020c)

The data strategy also plans a specific '**Common Europe Green Deal Data Space**' to support the Green Deal priority actions on climate change, circular economy, zero pollution, biodiversity, deforestation and compliance assurance and to initiate a '**GreenData4All**' initiative. This initiative will evaluate and possibly review the Directive establishing an Infrastructure for Spatial Information in the EU (INSPIRE), together with the Access to Environment Information Directive. Another action is the roll out of data services on a large scale to assist in collecting, sharing, processing and analysing large volumes of data relevant for assuring compliance with environmental legislation planned for 2021. In the area of circular economy, **digital 'product passports'** will be developed that will provide information on a product's origin, durability, composition, reuse, repair and dismantling possibilities, and end-of-life handling. In the context of the 'zero pollution ambition' where large amounts of data on chemicals exist, a pilot for the data strategy will be implemented in 2021. The **'Destination Earth'** initiative will build a high precision **digital twin** of the Earth as a digital monitoring platform to visualise, monitor and forecast natural and human activity on the planet. The sectoral data spaces offer additional opportunities related to the EGD for example in the following areas:

- in the transport sector: the review of the regulatory framework for interoperable data-sharing in rail transport in 2022;

- in the energy sector: actions for improving the interoperability in smart buildings and products, actions to improve their energy efficiency, optimise local consumption and broaden the integration of renewable energy sources; and

- in the agriculture sector: in 2019 Member States signed a declaration of cooperation titled 'A smart and sustainable digital future for European agriculture and rural areas', which recognises the potential of digital technologies for the agricultural sector and rural areas and supports the establishment of data spaces. In 2021, the Commission will take stock of the existing agricultural data spaces with Member States and stakeholders and decide on an EU approach.

The work on access to environmental data in the data strategy is not specifically focused on AI, but it is a prerequisite for AI applications to support the targets of the EGD.

The proposed '**Regulation on Data Governance'** (European Commission 2020f) is a key output of the data strategy. The regulation will support the set-up and development of common European data spaces in strategic domains, such as environment, energy, agriculture, mobility, finance, manufacturing and public administration. Sector-specific legislation on data access has also been adopted in some fields related to the EGD, e.g. smart metering information[13], electricity network data[14], or intelligent transport systems[15].

Regarding adverse impacts of AI, the EU Digital Strategy announced, "*initiatives to achieve climate-neutral, highly energy-efficient and sustainable data centres by no later than 2030*". To meet this goal, the Commission will rely on a mix of existing instruments and reviews of existing legislation such as:

- the Ecodesign Regulation on servers and data storage products;

- the EU Code of Conduct on Data Centre Energy Efficiency;

- the EU Green Public Procurement criteria for data centres, server rooms and cloud services; and

- the Energy Efficiency Directive, currently under review, which aims to set measures for the recovery of waste heat.

The EU Taxonomy Regulation[16] for sustainable investment includes a section on data processing including data centres and the Commission is currently conducting a study to address the lack of commonly accepted definitions and methods to assess the energy efficiency, climate neutrality and overall sustainability of data centres (European Parliament 2021).

Public and private Investment in AI research and innovation in Europe is still lower than in other regions (European Commission 2020b). In 2016 about $3 to 4 billion were invested in AI in Europe compared to around $8 to 12 billion in Asia and $15 to 23 billion in North America. This situation triggered the "**Coordinated Plan on AI**" developed with Member States with the aim to build closer cooperation, create synergies and maximise investment in the AI value chain in Europe. The new EU Multiannual Financial Framework for 2021-2027 is expected to strengthen the digital capacity through targeted programmes, in particular the **Digital Europe Programme** (DEP), the **Connecting Europe Facility** (CEF2), **Horizon Europe** and the **Space Programme**. In the DEP, €2.5 billion from a total budget of €7.6 billion are earmarked for AI. The digital strategy aims at boosting investments in AI research, innovation and adoption with a target of annual €20 billion in AI-related investment from the public and private sectors after 2020.

The DEP is the first financial instrument of the EU with the aim to bring AI to businesses and public administrations. DEP funding is also available for the European data space, safe access to and storage of large datasets and trustworthy and energy efficient cloud infrastructure. The programme also supports AI testing and experimentation facilities. However, it is not clear to what extent DEP funding will also prioritise the goals of the EGD. A key part of the DEP are European Digital Innovation Hubs. The extent to which the planned innovation hubs address environmental sustainability and the EGD goals should be a key criterion in the selection of applications.

Horizon Europe will fund a cluster on 'Digital, Industry and Space' with a budget of €15.349 billion which includes areas of invention on artificial intelligence and robotics in transport, agriculture, or energy, circular industries, low carbon and clean industries and the enhancement of services from

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[13]   Directive 2019/944 for electricity, Directive 2009/73/EC for gas meters.

[14]   Commission Regulation (EU) 2017/1485, Commission Regulation (EU) 2015/703.

[15]   Directive 2010/40/EU.

[16]   Regulation (EU) 2020/852 of the European Parliament and Council (2020).

Copernicus and Galileo for citizens and policy making (European Commission 2021a, 2021b). The cluster on 'Climate, Energy, Mobility' will receive €15.123 billion and the Cluster on 'Food, Bioeconomy, Natural Resources, Agriculture and Environment' €8.952 billion. The latter includes a focus area on 'agriculture of data'. The detailed programming activities of Horizon Europe have not yet been released to assess the extent to which these priorities include AI techniques and approaches. Data sharing will be a prerequisite for the funded research projects. Horizon Europe also includes a new partnership on 'Artificial Intelligence, Data and Robotics'. The CEF2 Digital programme supports and catalyses investments in digital connectivity infrastructures of common interest during the period 2021 – 2027 and creates a foundation in networks and connectivity for AI applications.

Thus, the EU key activities and the EU research agenda address both AI and the goals of the EGD as a priority and are in this respect quite advanced compared to Member States, where only Germany has set up research activities to specifically support AI related to the European Green Deal (see Section 4).

3.2. International Policies and Programmes

Many international initiatives on the relation of AI and the Sustainable Development Goals were started in the second half of the 2010s. They encompass public as well as private business or multi-stakeholder processes and can be differentiated in

- dialogues and partnerships to understand the potential and to further the development of AI to contribute to sustainable development;

- international cooperation supporting countries to harness AI for sustainable development; and

- initiatives for a common governance of AI to ensure its positive contribution to sustainable development.

Often these initiatives started as broader dialogues and then became more concrete and action oriented over time. However, most of them lack a focus on the environmental dimension and they do not cover it on equal terms with other legitimate development interests.

3.2.1. Dialogues and partnerships to understand the potential and to further the development of AI to contribute to sustainable development

In 2017 the UN started its '**AI for Good**' global summit series hosted by the International Telecommunication Union (ITU) in cooperation with other UN organisations envisaged as the leading dialogue platform on AI contributing to the SDGs. Over the years the summit series developed from a more traditional international conference into a platform with different formats for communication, exchange and learning. For example, as an outcome of the 2019 conference, the 'AI Commons' was launched to help connect AI adopters with AI specialists and data owners, to promote the sharing of collaborative frameworks as well as templates, roadmaps and examples of AI solutions for the common good, and to promote a common approach vis-à-vis AI resources, including data (AI Commons 2021). Also in 2019, a number of open focus groups were established, amongst them a 'Focus Group on Machine Learning for Future Networks, including 5G' and a 'Focus Group on Environmental Efficiency for AI and Other Emerging Technologies' tasked with identifying the respective standardisation needs. The thematic focus of the summit has shifted over the years: AI to solve environmental problems was included in the programmes, but often not very prominently, e.g. in 2017 only two of the showcased 23 applications, namely 'Global Fishing Watch' and IBM's project 'Lucy' on agriculture contributed to environmental objectives (ITU, 2017). Of the 16 Breakthrough Groups in the programme, none focused on an environmental theme. In 2020 with the Covid-19 pandemic, the series moved from yearly conferences to nearly weekly virtual events. While the overall thematic coverage broadened, only eight

of the more than 130 virtual events of the AI for Good series in 2020 and 2021 addressed environmental issues (ITU 2020a, Gates and Ma 2019).

In February of 2021, UNEP in collaboration with UNESCO, StartUp Inside and Microsoft launched a series of monthly virtual sessions on best practices of AI under the title '**AI for the Planet**'. Focus areas are climate change, nature and biodiversity, waste and pollution, and mobility.

Apart from processes like the ones described above, the UN publishes a yearly compendium on '**United Nations Activities on Artificial Intelligence**' showcasing their institutions' related initiatives (UN 2018, 2019, 2020). Furthermore, international organisations also set up platforms to enter and search for use cases, organisations, stakeholders and policies focusing on AI, like the **UN AI Repository** (ITU 2021) or the **OECD AI Policy Observatory** (OECD 2021).

A prominent multi-stakeholder initiative is the **'Partnership on AI'** already established in 2016 by the large US-based digital companies Amazon, DeepMind/Google, Facebook, IBM, and Microsoft. Its goals are "*first, to develop and share best-practice methods and approaches in the research, development, testing, and fielding of AI technologies; second, to advance public understanding of AI across varied constituencies, including on core technologies, potential benefits, and costs; third, to provide an open and inclusive platform for discussion and engagement on the future of AI, and to ensure that key stakeholders have the knowledge, resources, and overall capacity to participate fully in these important conversations and fourth to identify and foster aspirational efforts in AI for socially benevolent applications*" (Partnership on AI 2021). An important focus of the partnership is to build capacities, through research, discussions, educational material, etc., to understand and engage in discussions on the future of AI. By now the partnership comprises more than 100 organisations from 13 countries, of which more than half are non-profit entities including many professional associations, universities and think tanks but also UNICEF and UNDP. However, the partnership has not produced materials that address the environmental perspective of AI in a significant scope.

Another recent multi-stakeholder initiative is the UN Secretary-General's **Roadmap on Digital Cooperation** (UN 2020) where the primary objective is "*to firmly anchor environmental sustainability needs within the Digital Cooperation Roadmap and catalyse a digital planet for sustainability*". Specific objectives are to "*1. offer a vision and authoritative framing of the environmental sustainability and digitalisation nexus; 2. establish an acceleration plan [note of the author: by September 2021] for digitalizing environmental sustainability of including immediate priorities and partnerships covering a 2-3 year perspective; 3) help unite various environmental sustainability and digitalisation tracks under a common framework and federation umbrella to improve coordination, coherence and impact and 4) mobilize the scientific community and prioritize a research agenda*" (UNEP 2021).

Given the potential and relevance of using satellite data for achieving environmental objectives and the potential of AI for the interpretation of satellite imagery, another potentially relevant multi-stakeholder initiative is the **Open UN GIS Initiative** and therein the **GEO-AI Working Group 5**. It started work in September 2020 and is co-chaired by UN Global Pulse and FAO. The working group's activities "*to research, elaborate and adopt innovations, best practices, and recommendations to […] research AI applications and methodologies that can support geospatial analysis, including image interpretation; promote interoperability between opensource AI and GIS frameworks; enhance and develop opensource standards and tools for the wider AI and GIS communities*", could be especially relevant for environmental purposes (UN Global Pulse, FAO 2020).

With the **Open for Good Alliance**, UNESCO and partners are addressing to overcome a shortage of locally relevant training data and to address technical questions by initiatives which work on access to AI. The alliance hence is working on increasing the availability and quality of openly available,

representative and non-discriminatory data, specifically localised training data for local AI development in Africa, Asia and beyond (Open for Good 2021).

The **OECD** supports governments by measuring and analysing the impacts of AI technologies and also elaborates recommendations related to policy and institutional frameworks for AI as well as AI principles (see below). In addition, the above-mentioned OECD Policy Observatory on AI provides a useful resource for the development of respective policies. The Policy Observatory includes a category for AI and the environment which indicates that besides five EU Member States (Germany, Netherlands, Denmark, Portugal), relatively few other countries have policy initiatives for AI related to the environment (China, India, Japan, Korea, Australia with each one initiative and UK with two initiatives).

Besides the work of the intergovernmental organisations, there are many other international activities. **Climate Change AI** (CCAI) is an organisation composed mainly of researchers, engineers and industry who believe that machine learning can play an impactful role related to climate change. The organisation aims at building a community of diverse stakeholders, advance the discussion and provide advice, develop educational resources and programs and fill gaps in essential infrastructure such as funding, tools, and datasets (Climate Change AI 2021). This organisation has compiled the largest structured analysis of scientific publications related to AI and climate change (Rolnik et al. 2019).

3.2.2. Initiatives for a common governance of AI in order to ensure its positive contribution to sustainable development

The first intergovernmental standards on AI were developed and agreed upon by the OECD Member States and additional countries in May 2019. The principles for AI adopted by the G20 in June 2019 have been "drawn from the OECD Recommendation on AI" (G20 2019). The OECD principles focus on responsible stewardship and trustworthiness of AI. They focus on i) orienting AI towards inclusive growth, sustainable development and well-being, ii) basing AI on human-centred values and fairness, iii) permitting transparency and explainability, iv) ensuring robustness, security and safety, and v) calling for accountability. However, they only touch upon the environmental dimension of sustainable development with one short reference, stating that "*Stakeholders should proactively engage in responsible stewardship of trustworthy AI in pursuit of beneficial outcomes for people and the planet, such as [...] protecting natural environments [...] thus invigorating inclusive growth, sustainable development and well-being*" (OECD 2021). They also prescribe that "*AI actors should [...] apply a systematic risk management approach to each phase of the AI system lifecycle [...] to address risks related to AI systems including privacy, digital security, safety and bias*" but do not mention environmental risks in the examples given. While their general scope allows for adherence by countries around the globe, the principles provide little guidance or safeguards for an ecologically sustainable development and operation of AI. The G20 principles do not go beyond this either.

In 2018, the Secretary General of the United Nations initiated his Roadmap for Digital Cooperation process by setting up a High Level Panel on Digital Cooperation and commissioning it "*to consider how digital cooperation can contribute to the achievement of the Sustainable Development Goals*" and "*to consider models of digital cooperation to advance the debate surrounding governance in the digital sphere.*" The resulting report 'The age of digital interdependence' contained the broad recommendation that AI systems "*should be designed in ways that enable their decisions to be explained and humans to be accountable for their use. Audits and certification schemes should monitor compliance of AI systems with engineering and ethical standards, which should be developed using multi-stakeholder and multilateral approaches*" (Gates and Ma 2019).

Adding to various ethical frameworks with a more limited scope, UNESCO is currently working on a set of recommendations on the ethics of AI that aims to go beyond values and principles by also including

concrete policy recommendations. The recommendations are scheduled to be adopted by UNESCO's General Conference at its 41st session at the end of 2021. They include a framework for operationalisation, including through ethical impact assessments to address the challenges and opportunities of AI for all individuals and communities for which UNESCO is planning to support Member States in developing a globally accepted methodology for Ethical Impact Assessment (EIA) of AI technologies. The assessments are thought to encompass an ex-ante level to avoid discrimination in the selection of datasets and programmers' design choices and to make transparent the values informing these choices and an ex-post level monitoring outcomes that could infringe individual rights (UNESCO 2019).

From an environmental sustainability perspective, the first draft of the recommendation on the ethics of artificial intelligence goes beyond the OECD principles. Consideration of the environmental perspective and aspects can be found throughout the whole document: 'Environment and ecosystem flourishing' to be recognised and promoted by AI is listed as the second item in the section on values. There, the recommendations reiterate the obligation to follow the precautionary principle and call for AI actors to reduce the environmental impact of AI systems. In the section on principles, the principle 'sustainability' calls for "*the continuous assessment of the social, cultural, economic and environmental impact of AI technologies*" oriented by the SDGs. The draft recommendations also include a subsection on 'environment and ecosystems' urging to "*assess the direct and indirect environmental impact throughout the AI system life cycle, including but not limited to, its carbon footprint, energy consumption, and the environmental impact of raw material extraction for supporting the manufacturing of AI technologies*" and proposing to apply data, energy and resource-efficient AI methods. In addition, appropriate evidence should be required proving that an AI application will have the intended effect or accompanying safeguards will ensure so. The subsection further calls on Member States to "*introduce incentives […] to ensure the development and adoption of rights-based and ethical AI-powered solutions for disaster risk resilience; the monitoring, protection and regeneration of the environment and ecosystems; and the preservation of the planet*" supporting "circular economy type approaches and sustainable consumption and production patterns" (UNESCO 2020).

A very recent initiative to support the dialogue on international cooperation and global governance for AI was launched by Tsinghua University in China and supported by the UNDP. The inaugural International AI Cooperation and Governance Forum took place in Beijing in March 2021. It aims to become the leading platform for global level discussions on AI governance and international cooperation. The forum illustrated the unanimous view that global AI governance is indispensable (UNDP 2020).

The need for more global governance is also highlighted in the recent World Development Report 2021 focusing on data. The report highlights the essential role of datasets as prerequisites and basis for AI applications and the economic interests posing challenges for open access to data and/or sharing of data. It states that "*a global consensus is needed to ensure that data are safeguarded as a global public good and as a resource to achieve equitable and sustainable development.*" It goes on referencing the increasing number of voices, calling for "*some sort of global charter or convention […] to realize the benefits of data in a safe and secure way and to avoid destructive beggar thy neighbor strategies*", be it a 'Bretton Woods for AI' (Rockefeller Foundation) or a 'Digital Geneva Convention' (Microsoft) (World Bank 2021).

4. CURRENT TRENDS AND BEST PRACTICES IN AI POLICY AT MEMBER STATE LEVEL

In 2018, the Coordinated Plan on AI was published in which Member States and the Commission agreed to enhance Europe's competitiveness related to AI and to deal with social, economic, ethical and legal questions (European Commission 2018). In addition, all Member States agreed to establish an AI strategy. The coordinated plan also established AI Watch, the European Commission's knowledge service to monitor the development, uptake and impact of AI for Europe. The European Commission also collaborates with the OECD on analysing National strategies on AI and exchange on their respective platforms, being the OECD AI Policy Observatory and AI Watch. Member States often use different titles for their strategies or action plans on AI and the documents are not very comparable with regard to their content, length and focus areas, which also limits the following analysis of national strategies of Member States to some extent.

From 27 Member States, four (Croatia, Greece, Ireland, Romania) have not yet developed final AI strategies. Out of the remaining 23 Member States, eight strategies (Austria, Estonia, Latvia, Cyprus, Czech Republic, Luxembourg, Poland, Slovakia) do not focus on EGD priorities or do not mention specific initiatives to promote AI applications related to environmental problems.

From the remaining 15 national AI strategies, nine strategies include priority or focus areas for AI applications related to environmental problems, e.g. increase energy efficiency or energy management, sustainable agriculture solutions, sustainable transport, smart and sustainable cities that address environmental issues (Belgium, Bulgaria, Finland, Latvia, Lithuania, Malta, Portugal, Slovenia, Spain, Sweden). The most frequently mentioned area is agriculture and the intention to develop precision farming. Smart traffic management to avoid traffic jams and optimisation of urban transport as well as smart grids in the energy sector and smart and sustainable cities are other focus area that appear in many strategies.

The strategies of six Member States go beyond such priority areas:

Denmark intends to be a frontrunner, using AI to support the green transition. The country developed the following priority approaches (Danish Government 2019):

- The public sector should benefit from an intelligent environmental monitoring, prediction of flooding during cloudburst events and management of drainage systems.

- The Danish government will identify five public-sector datasets, which can be made available for businesses, researchers and public. The datasets will not contain personal data, but rather environment and climate data from the transportation sector.

- Through membership of ESA, Denmark is also helping to gather and process large amounts of weather, environment and climate data. Most of this data is freely available for citizens, businesses, public authorities and researchers.

In addition, the following priority areas were identified:

- Energy and utilities: Use of AI to develop new products, services and business models. The products can help other businesses as well as consumers to optimise their energy consumption and thereby reduce their costs and carbon footprint.

- Agriculture: AI to support the development of precision agriculture in order to continue sustainable agriculture in Denmark.

- Transport: In the transport area, AI can be used to ensure better and more timely public transport. Furthermore, new solutions can be developed to optimise traffic management to benefit users of both public and private transport.

A number of specific projects have been established in Denmark related to AI and EGD topics. The Danish funding for the AI strategy with 24 initiatives has been set at €9.2 million for the period 2019-2027. The budget has since been reprioritised and lowered to €5 million.

Hungary also committed in its national AI strategy to develop AI to be high-tech and green. Hungary is the only Member State with quantified environmental targets in the AI strategy (Ministry for Innovation and Technology et al. 2020). Due to the use of data-based systems, the emissions of ammonia in agriculture should decrease by 32% by 2030. By 2030, 70% of the scheduling of renewable energy production should be carried out by smart technologies.

Hungary's AI strategy includes **transformative programmes** which address several areas of the EGD:

- climate-driven agriculture: AI to help mitigate adverse impacts of climate change in agriculture;

- development and application of AI-based, optimisation solutions in terms of plant production and stock farming, implementation of predictive, AI-based analytics methods to improve water, soil and air quality to enhance the efficiency of management;

- establishment of an agricultural data framework system including environmental data to enhance efficiency of government operations and develop new services for farmers; and

- implementation of smart grid technologies to facilitate the creation of a more accurate production timeline for weather-dependent renewable energy sources and the operation of the energy network.

In addition to the transformative programmes, focus areas include sector-specific focus on smart and environmentally conscious manufacturing, AI-based, automatic traffic management to reduce traffic jams, optimisation of urban public transport networks, passenger counts, journey optimisation, introduction of smart heating cost sharing for apartments using central or district heating services and the development of data-driven energy market models.

France's national AI strategy also includes a strong commitment to use AI opportunities in the environmental area to contribute to a smart ecological transition (President of the French Republic 2019). Priority areas are:

- transport: zero-emission urban mobility;

- agriculture: development of monitoring tools for farmers will pave the way for smart agriculture benefiting the entire agrifood chain; and

- making AI more environmentally friendly.

France also outlines specific initiatives and actions in this area:

- it intends to create a research centre focusing on AI and the ecological transition;

- it wants to implement a platform to measure the environmental impact of smart digital tools and supports the ecological transition of the European cloud industry and reduce energy consumption of AI; and

- it promotes free access to ecological data.

France provides €1.5 billion to the development of artificial intelligence by the end of 2022, including €700 million for research, which are about €100 – 500 million per year. There is no budget breakdown related to the environmental applications of AI.

Italy's national AI strategy also has the clear objective that AI should support the implementation of the Sustainable Development Goals (Ministry of Economic Development 2019). Priority sectors in the strategy are:

- environment, infrastructures and networks: AI solutions to achieve savings in the use of resources (water, electricity and natural gas), reduction in polluting emissions (e.g. monitoring and intelligent management of networks and consumption), strengthening of the circular economy (e.g. monitoring and predictive management of the waste cycle), better prevention of natural disasters;

- agri-food sector: avoiding overproduction and waste, precision agriculture, optimisation of food processing, storage and transport processes; and

- smart cities: intelligent parking, traffic management and control of signs, management of lighting and optimisation of public transport.

Italy started the initiative 'trust for sustainability' which promotes pilot projects on the issues of social and environmental sustainability, in which public and private organisations in possession of data temporarily entrust the management to certified third parties for the pursuit of a public interest.

The **Netherlands**' AI strategy also includes a commitment to exploiting the social and economic opportunities of AI in domains and sectors such as agriculture and food, and the energy transition and sustainability. The Dutch priorities and actions are:

- Agriculture and food: further automation, precision agriculture, and system integration, And the development of a data infrastructure for arable farming. The JoinData Foundation was set up from the Smart Dairy Farming project, a non-profit cooperative that enables safe and transparent data distribution in the food & agriculture sector.

- Energy transition: implementation of smart solutions to make use of the various variable renewable energy sources. In the Netherlands, solutions have been developed for these types of flexibility and congestion markets, ranging from energy source selection in buildings, the role of electric cars in the energy system, fault detection in electricity networks and providing insight into the energy networks. The wind farms in the North Sea are also subject to AI approaches, such as inspections with drones, maintenance robots and the vertical driving of foundations.

In the Dutch version of the strategy, an annex mentions that the yearly governmental budget to AI innovation and research is estimated at €45 million.

The **German** national AI strategy includes a strong focus related to the topics of the EGD – both in Germany and across the world (Federal Government 2020). In the OECD AI policy database, Germany is the country with the most AI policy actions related to the environment. The German government will develop a concept for the **environmental impact assessment** of AI and step up its funding for research on the environmental impacts of AI, in particular commissioning the collection of empirical data and a systematic analysis of the CO_2-saving potential of AI, duly taking into account possible negative effects (such as rebound effects).

The German government will set up an 'Application Lab for AI and Big Data' with the aim of developing data-based applications to attain the Sustainable Development Goals. Germany also plans to provide

a cloud for environmental data to ensure that valid access to this data is available to scientists, businesses and society in a transparent way, and to enable the development of sustainable AI applications.

The Federal Government has initiated several research projects on AI in **agriculture**. These include digital trial fields in agriculture, which show how digital and AI technologies can be optimally deployed to protect the environment, improve animal welfare and biodiversity, and facilitate work. The Federal Government also plans to provide funding for the establishment of an application hub in the field of **recycling and the circular economy**. The aim and objective of the hub's research and development work is to use AI-supported recycling-friendly product design, smart sensors and tracking technologies for collection, sorting and recycling to increase the use of recyclates, to use plastics longer and more efficiently and to avoid plastic being released into the environment.

To enable the administration to use AI in a legally compliant way quickly and to effectively support the goal of 'sustainable AI' as an important component of sustainable digitalisation, environmental law is being examined to see whether modifications might make sense. Germany has also started a cooperation with France in bilateral AI clusters focusing on specific industries (e.g. healthcare, environment, robotics, mobility).

Germany is the only Member State to published data on **specific funding activities related to AI and environmental solutions**. Germany will fund AI applications to benefit the environment and the climate and will develop assessment principles for this. The goal is to **initiate 50 flagship applications** in this field. Funding: **€3 billion in period 2019-2025**. The funding initiative AI Flagship Projects focussing on funding AI innovations for climate protection and the resource efficiency of AI applications started in 2019 with a volume of €27 million. 13 projects are currently funded under the title 'KI for the environment" and 13 projects in the area of 'application, scaling and capacity building'.

While these national AI strategies were triggered as part of the EU's coordinated plan on AI to avoid fragmentation and become more powerful, it is striking that some national AI strategies lack a European dimension and only outline how the country itself intends to become an AI leader, without providing links to the many relevant EU policy activities. This may be partly due to the fact that many EU policy initiatives have been released recently and national AI strategies may have been developed before. The perspective that European cooperation is essential to be a global player with influence on AI development and implementation is sometimes missing in the strategies. However, some strategies strongly build on the EU's activities and priorities and have been prepared in the spirit of European cooperation.

5. RECOMMENDATIONS

AI systems and applications have a broad range of significant potential to support a socio-ecological transformation, their deployment can also result in serious and far-reaching environmental risks. Environmental policy and regulation in principle have a broad spectrum of instruments at their disposal to enable the development of technologies and innovations in a goal-oriented manner, as well as to protect and take precautions against specific sustainability risks.

5.1. Strengthen research on AI systems and their applications for the goals of the European Green Deal

The EU has already set the right priorities in its new EU Multiannual Financial Framework for 2021-2027 to strengthen digital capacity through the Digital Europe Programme (DEP), the Connecting Europe Facility (CEF2), Horizon Europe, and the Space Programme. In particular Horizon Europe includes key research programmes on AI in relevant sectors linked to environmental objectives. The DEP is focused on more general strategic areas and it is less clear to what extent it will benefit AI applications in all areas of the EGD with testing and experimentation facilities or data spaces Thus, further implementation should ensure that this focus is fully reflected. It will be important to ensure coordination among the four key EU research programmes for an effective funding across all the diverse topics of the EGD.

The research agenda in the 2021-2027 period must play a key role in advancing research on how AI can make ICTs more energy-efficient, using demonstration projects related to energy-efficient data centres to achieve the EU's target of climate-neutral, highly energy-efficient and sustainable data centres by no later than 2030.

Without control and steering, there is the risk that AI-based research and consequently technologies with potential to achieve certain sustainable development goals may not be prioritised, if their expected economic impact is not high. As the study showed, there are many options for AI solutions to benefit the objectives of the EGD. While in some areas it will be difficult to incorporate AI solutions into business models (e.g. related to the protection of biodiversity, nature conservation, environmental monitoring activities), in others where such business models already exist these will not automatically contribute only positively to achieving environmental objectives (e.g. precision agriculture). It is therefore important that EU research programmes provide resources for work on those potential applications in environmental areas that may be more difficult to turn into business cases and that may not be undertaken without public funding. This is particularly relevant for AI applications for environmental monitoring or for the enforcement of environmental law.

The EGD requires transformative changes in several sectors which have been outlined in the EU strategies. Research on AI methods to enhance the EGD objectives should particularly address the areas where such transformative changes are required.

It is also important that research activities deliver replicable AI solutions to cater for the needs of the public sector and local governments related to AI and the topics of the European Green Deal. Many local governments in the EU will neither be in a situation where they can afford to procure AI solutions on environmental issues, nor will they have strong staff capacities in this area to plan for the design of such AI solutions. This should also be taken into account in the EU research programmes in the period 2021-2027.

To use the potential of AI for earth observation on environment-related issues it is necessary to strengthen capacities of researchers in the EU that are familiar with both AI and earth observation, to

provide clean quality-controlled training datasets, easy access to observation data and the development of further use cases and prototype applications.

5.2. Develop, promote and implement methodologies for environmental impact assessments of AI technologies

As an approach to operationalising the various initiatives to establish and apply ethical values and norms for AI applications, the EU should promote or require new AI systems to undergo impact assessments that sufficiently cover environmental sustainability criteria prior to their large-scale use. Such assessments should go beyond the direct environmental impact of the AI system itself (raw materials, energy use) and cover also indirect impacts of the use and operation of the AI application. While these impacts will be more difficult to assess, respective methodologies could draw upon the family of approaches of policy impact assessments, sustainability impact assessments or strategic environmental assessments. Such assessments would increase transparency on the functioning and environmental impacts of AI systems. They would also help build experience with the possibilities, limitations and practical implementation of such assessments. Both transparency on the functioning and impacts as well as methodological experience are important aspects of an ecological regulatory framework for AI systems.

To ensure that AI systems developed by the private sector adhere to sustainable development principles, audit and certification mechanisms for AI systems could be developed covering the direct environmental footprint of their development and operation and the environmental, social and human rights impacts of their functionality and application (through the triggered changes in behaviour of individuals, production units and processes, logistics, companies, etc.). Such certification schemes could, in a second step, also be used to facilitate the integration of sustainable development goals in public procurement processes of large-scale AI systems and applications.

5.3. Further monitoring and evaluation of trends required

The EU should promote projects and initiatives that monitor and collect the current AI activities in the EGD priority areas in a more systematic way and assess and evaluate the environmental, social, legal and ethical implications. The initial findings in this study show that for key areas for greenhouse gas mitigation we did not find any examples of AI applications, such as to reduce greenhouse gas emissions from livestock which is the largest emission source in agriculture. It would be important to evaluate such gaps in a more systematic way than has been possible in this study.

Based on such systematic evaluation, gaps could be filled through EU research programmes and very promising AI applications could be further promoted. For example, the EU could establish more specific objectives related to the use of promising AI applications for the EGD priority areas, in a similar way as Hungary in its national strategy. An example would be to set an objective date by when a certain share of the EU electricity grid should be managed by AI technologies to integrate flexible renewable energy supply and demand and storage options, which is a key future requirement for a carbon-neutral Europe.

Many of the AI applications that support the EGD targets enhance the efficiency of existing systems or practices such as electricity grids, fertilisation, or transport management. Transformational changes needed to achieve the objectives of the EGD cannot be extrapolated from the past. Machine learning trained on large amount of historic data thus may not be able to forecast necessary transformational changes and may prefer systems and stages that we currently seek to overcome. Much more

sophisticated technologies than machine learning would be necessary to respond to the current challenge.

AI systems are unevenly distributed between stakeholders in sectors or between countries. For instance, complex AI-enhanced agricultural equipment may not be accessible to small farmers and thus produce an increased gap in its use with respect to larger producers. This could enhance the existing social impacts on smaller farms in the EU or increase uneven distribution effects between richer and poorer countries and could further support the growth of particularly large farms and their business model on large scale monocultures including their detrimental environmental effects.

5.4.   Empower transformative systems and applications in digital markets

The purpose for which AI systems are developed and utilised is critical to foreseeing whether they will make their decisions in accordance with environmental goals. It is thus plausible that sustainable policies focus on capacitating stakeholders of (environmental) public interest who develop and apply AI systems in line with sustainability goals. It also makes sense to provide private sector actors with incentives to develop AI applications which are designed to achieve environmental goals. Such indirect strategies of environmental regulation can be put forward in a number of ways.

Incentives for developing and operating sustainable AI-applications could be created by further aligning funding policies with sustainability goals and respective taxonomies or by means of 'green' adjustments of public procurement. Further development of 'green' procurement policies could create additional incentives for the development and use of promising AI applications, e.g. for sustainable supply chain management and trustworthy certification.

Economies of scale or vendor lock-in effects can make it difficult for sustainable applications to compete against commercial providers. For AI applications with particular potential for the environment, consideration should therefore also be given to prioritising the development and operation of certain applications by public actors.

5.5.   Explore, develop and promote a European model of the data economy harnessing data as a resource for sustainable AI

Related to environmental issues, it is essential to support open access to relevant data and initiatives working to enlarge the open datasets. This allows thematic fields to be covered that do not necessarily present an easy business case and the inclusion of neglected geographical regions and countries. As the World Development Report (World Bank 2021) states: "*a global consensus is needed to ensure that data are safeguarded as a global public good and as a resource to achieve equitable and sustainable development.*" The 'Common Europe Green Deal Data Space' to support the Green Deal priority actions on climate change, circular economy, zero-pollution, biodiversity, deforestation and compliance assurance and the start of the 'GreenData4All' initiative as part of the EU data strategy are important steps in this direction.

In relation to AI, access to relevant, high-quality, labelled and structured environmental data, both to train algorithms and to use as input data, will be instrumental to the development of AI applications relevant for achieving the EGD. New mechanisms for sharing relevant datasets will need to be tested and developed, and efforts are needed to ensure high-quality data labelling. Large scale, open source data resources are one option which could be explored further as a mechanism for providing the high-quality data required to develop specific AI systems. The broad development of AI applications for environmental purposes will strongly depend on the sharing of data and on access to data which has to be organised, regulated and financed. It is important to provide funding within the EU's research

programmes (Horizon Europe, Digital Europe Programme) for the preparation of such structured environmental datasets.

The European Data Strategy and the draft Data Governance Regulation emphasise the importance to ensure better access to data. However, emphasis is often placed on improving the conditions for the (voluntary) sharing of data between companies as well as on individual 'data donations', and on the widest possible access to public databases ('open data'). Strong legal protection of privately held data, e.g. as trade secrets, may be an obstacle to many use cases of AI for environmental governance and administration. A European legal act announced for 2021 will also include an assessment of the intellectual property rights framework, with a view to further improving data access and use. Different use cases of data for environmental goals should be considered as well.

The way in which access to data is organised – i.e. how data is shared and how authority and control over data is allocated – is fundamental for the design of AI systems and the outcomes of AI decisions. Recent proposals and debates about democratic data governance or representative data rights might indicate legal and organisational pathways for data allocation, which reflect principles of sustainability

Trustworthy procedures and a clear allocation of citizen's rights to control the use of data could also facilitate applications directed towards socio-ecological goals. Data regulation can create incentives to share or generate high-quality data. In this context, for example, the introduction of registered 'data altruism organisations' under the recently proposed European Data Governance Regulation may harness potential for the EGD.

5.6.　More Member States should integrate the European strategy into their national AI strategies

While national AI strategies have been triggered as part of the EU's coordinated plan on AI to avoid fragmentation and become more powerful, it is striking that only six Member States have included a stronger focus on AI applications for the targets of the EGD. The coordinated plan will not achieve the relevant impacts if Member States do not follow the Commission in these priorities. Some Member States' national AI strategies do not sufficiently reflect EU policy initiatives and EU cooperation and further efforts are needed to implement enhanced cooperation in the EU related to AI.

Despite the proposed 'Common Europe Green Deal Data Space' in the data strategy, Member States also identified such priority data spaces and datasets which they plan to provide for businesses, researchers and the public. Despite the efforts of the EU's coordinated plan on AI, the analysis of Member States' strategies indicates that further coordination on such data spaces is needed in order to avoid a scattered and fragmented situation with a large number of data spaces, but few relevant data in these spaces.

5.7.　Push the EU agenda for AI to support environmental sustainability at the global level

Since most international initiatives on AI do not focus on environmental use cases, discuss and analyse environmental risks or develop policy recommendations to safeguard environmental objectives in the use of AI, the EU could fill this gap. It could do so by joining, strengthening and at the same time broadening the UNEP's AI for the Planet initiative or the Coalition for Digital Environmental Sustainability (CODES) or by starting an own international initiative. Another approach could be to get involved through suitable agents in initiatives like the AI partnership or the AI for Good initiative to ensure that these increasingly integrate environmental goals.

Developing countries must also be supported in building the necessary capacities within research, business, government and civil society to participate in and benefit from the further development of AI for tackling environmental problems. Developing and emerging economies successfully combatting the drivers of the deterioration of global environmental goods like biodiversity or climate is becoming increasingly vital. Hence, it is crucial that the potential of AI is accessible to these countries. However, there are still major obstacles to doing so, such as the insufficient availability of local data, access to relevant data, a limited skills base, limited attractiveness for respective business models or limited capacities within governments to promote and to regulate AI development and use.

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Artificial Intelligence (AI) can be deployed for a wide range of applications to promote the goals of the European Green Deal. However, adverse environmental impacts of AI could jeopardise the attainment of these goals. The report describes environmental potential, clarifies characteristics and causes of environmental risks, and outlines initiatives and best practices for environmental policies. It illustrates the need for regulatory action to align design and deployment of AI with the goals of the European Green Deal and concludes with specific recommendations.

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