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The Role of Artificial Intelligence in achieving Environmental Sustainability for the Health and Technological Industry

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Master Degree in Social Studies of the Environment and Sustainability

Supervisor:
PhD, Prof. Vasco Barroso Gonçalves Assistant Professor
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October, 2024

CIÊNCIAS SOCIAIS
E HUMANAS

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Dedicated to all living things – to the ones of the past, the present and the future.

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I wish to express my deepest gratitude to my family – my mother Maria, father António, and sister Andreia – my close friends, and especially my love Liliana, for the unwavering support during the countless weekends dedicated to creating, developing and completing this research work on AI-based Environmental Sustainability, a long-held aspiration and dream of mine.

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Finally, I am grateful for the inspiration that music brings to all of us, and particularly, to my heart and soul. Thank you all.

Resumo

A Inteligência Artificial (IA) representa uma tecnologia fundamental que está a moldar diversos sectores a nível global. Este trabalho explora o panorama complexo e multifacetado da IA, incluindo os seus principais conceitos, evolução, aplicações transformadoras, e a sua relação com os Objetivos de Desenvolvimento Sustentável (ODS). A análise do papel da IA nos setores da saúde e da tecnologia com base em evidências empíricas, permite comprovar a sua aplicabilidade e potencial transformador, assim como identificar as soluções com base em IA cuja missão é enfrentar desafios ambientais. A revisão da literatura permite adicionalmente conhecer a relevância dos quadros regulamentares que regem presentemente a IA a nível nacional, europeu e internacional.

Através de uma abordagem de métodos mistos, incluindo a criação de um inquérito online dirigido a profissionais do setor, este estudo identificou padrões na implementação de soluções de sustentabilidade ambiental com base em IA, nas indústrias da saúde e tecnologia. Os resultados do inquérito revelaram que 57% das organizações utilizam *Machine Learning* (ML) como principal capacidade de IA, e que 70% dos inquiridos aplicam estas tecnologias para a recolha e análise de dados ambientais. A análise da pegada de carbono e de estratégias de redução de emissões de Gases de Efeito Estufa (GEEs) emergiram como o serviço mais oferecido, representando cerca de 61% das respostas. Porém, o estudo também identificou alguns desafios existentes nos dias de hoje, em que 43% dos inquiridos apontaram para a qualidade e integridade dos dados como principal obstáculo à implementação da IA neste setor. Relativamente ao impacto das soluções baseadas em IA, os resultados demonstram uma taxa média de sucesso de 37% no envolvimento comunitário e com variações significativas na redução de emissões de GEEs, com valores entre 8% a 70%.

As perspetivas futuras mostram-se altamente promissoras, com cerca de 66% dos inquiridos a preverem um impacto significativo da IA nas práticas de sustentabilidade num horizonte de 1 a 5 anos. Os principais focos de desenvolvimento identificados incluem a abordagem a riscos ambientais emergentes (35%), a melhoria da eficiência das práticas de sustentabilidade (27%) e o escalar progressivo de soluções existentes (24%). Esta investigação espera, desta forma, contribuir para o avanço do conhecimento sobre o papel transformador da IA na implementação e melhoria das práticas aplicadas em sustentabilidade ambiental, oferecendo evidências empíricas e perspetivas práticas para os decisores-chave, entidades governamentais, investigadores e todos os profissionais que operam na intersecção entre a tecnologia, a sustentabilidade e a saúde.

Palavras-chave: Inteligência Artificial; Sustentabilidade Ambiental; Indústria da Saúde; Indústria Tecnológica.

Abstract

Artificial Intelligence (AI) represents a fundamental technology that is shaping various sectors globally. This work explores the complex and multifaceted landscape of AI, including its core concepts, evolution, transformative applications, and its relationship with the Sustainable Development Goals (SDGs). The analysis of AI's role in the health and technology sectors, based on empirical evidence, validates its applicability and transformative potential, as well as AI-based solutions designed to address environmental challenges. The literature review also reveals the relevance of regulatory frameworks currently governing AI at a national, European, and international levels.

Through a mixed-methods approach, including the creation of an online survey directed at sector professionals, this study identified patterns in the implementation of AI-based environmental sustainability solutions in the health and technology industries. Survey results revealed that 57% of organizations use Machine Learning (ML) as their primary AI capability, and 70% of respondents apply these technologies for environmental data collection and analysis. Carbon footprint analysis and Greenhouse Gases (GHGs) emission reduction strategies emerged as the most offered service, representing approximately 61% of responses. However, the study also identified several present-day challenges, with 43% of respondents indicating data quality and integrity as the main obstacle to AI implementation in this sector. Regarding the impact of AI-based solutions, results demonstrate an average success rate of 37% in community engagement adding to significant variations in GHGs emissions reduction, obtaining results between 8% and 70%.

Future perspectives appear highly promising, with approximately 66% of respondents predicting a significant impact of AI on sustainability practices within a 1-to-5-year horizon. The main development focuses identified include addressing emerging environmental risks (35%), improving the efficiency of sustainability practices (27%), and progressively scaling existing solutions (24%). This research thus aims to contribute to advancing knowledge about AI's transformative role in implementing and improving environmental sustainability practices, offering empirical evidence and practical perspectives for key decision-makers, government entities, researchers, and to all professionals operating at the intersection of technology, sustainability, and health.

Keywords: Artificial Intelligence; Environmental Sustainability; Health Industry; Technological Industry.

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List of Abbreviations

AI – Artificial Intelligence

AGI – Artificial General Intelligence

AMA – Administrative Modernization Agency

ºC – Degrees Celsius

CBD – Convention on Biological Diversity

CDSS – Clinical Decision Support Systems

CO_2 – Carbon Dioxide

COVID-19 – Coronavirus disease 2019

CT – Computed Tomography

DL – Deep Learning

DT – Digital Twins

ESG – Environmental, Social, and Governance

EC – European Commission

EU – European Union

GDPR – General Data Protection Regulation

GHG – Greenhouse Gas

GRI – Global Reporting Initiative

HW – Hardware

HITL – Human-in-the-loop

IoT – Internet of Things

IPCC – Intergovernmental Panel on Climate Change

ML – Machine Learning

MRI – Magnetic Resonance Imaging

NLP – Natural Language Processing

R&D – Research & Development

SDGs – Sustainable Development Goals

SW – Software

OECD – Organisation for Economic Co-operation and Development

UN – United Nations

UNESCO – United Nations Educational, Scientific and Cultural Organization

UNFCCC – United Nations Framework Convention on Climate Change

WEF – World Economic Forum

CHAPTER 1

Introduction

Chapter 1 establishes the introductory foundation for examining AI's role in achieving environmental sustainability goals, with an overview of the current landscape, presenting the urgent need for innovative solutions to environmental challenges and AI's potential in addressing them. It is then followed by the research objectives and questions that guide this investigation, focusing on understanding AI's capabilities, regulatory frameworks and practical applications in environmental sustainability. The chapter concludes with a research framework that outlines the structure of this thesis, providing a roadmap for the comprehensive examination of AI's implementation in environmental sustainability initiatives.

1.1. Introductory Overview

AI stands at the forefront of technological innovation in addressing global environmental challenges, particularly within the health and technology sectors. In the context of growing environmental awareness and the urgent need to mitigate climate change by reducing carbon emissions, the medical and tech industries face a pivotal moment. The integration of AI and related technologies emerges as a potent catalyst for driving sustainable innovation and mitigating the environmental impacts associated with their operations. AI not only enhances operational efficiencies but also facilitates informed decision-making processes crucial for achieving carbon neutrality and reducing environmental footprints. The current paradigm demands a proactive approach to addressing environmental challenges that threaten the sustainability of our planet. As concerns about climate change intensify, companies are called on to take concrete steps to reduce their carbon footprints and promote more sustainable business practices. In this context, AI emerges as a revolutionary tool, capable of offering innovative solutions to environmental problems, while driving efficiency and technological progress.

The world confronts a formidable challenge in combating climate change and achieving net-zero emissions, crucial milestones to curtail global temperature rise. This imperative underscore the critical roles of renewable energy and AI technologies in advancing environmental sustainability efforts across industries. Renewable energy technologies offer a sustainable alternative to fossil fuels, contributing significantly to reducing GHGs emissions. However, the intermittent nature and other challenges of renewable energy integration necessitate advanced solutions like AI to optimize energy production, storage, and distribution (Hassan et al., 2023).

The medical and technology industries which are pivotal to global economic dynamics, are also substantial contributors to carbon emissions. As of 2021, global CO_2 emissions have reached record highs, with countries like China, the United States of America and India leading in emissions. Despite international agreements like the *Paris Agreement* aiming to limit global warming, many nations still struggle to meet emission reduction targets, revealing gaps in political agreements and cooperative efforts (Hassan et al., 2023).

AI's application in these sectors holds promise for enhancing environmental sustainability by optimizing resource utilization, improving energy efficiency, and reducing carbon footprints. By leveraging AI-driven analytics and predictive modeling, organizations can strategize better to achieve environmental goals while maintaining technological advancements and economic growth (Bajwa et al., 2021; Hassan et al., 2023; Nishant et al., 2020; Park et al., 2020).

Therefore, this research sets out to outline a comprehensive framework for the effective implementation of AI on these fields, aiming not only at operational efficiency but also at long-term sustainability. By highlighting the tangible benefits and challenges underlying this approach, this thesis aims to contribute to the development of strategies and policies that promote the widespread adoption of AI as a catalyst for positive change for the environment and worldwide societies.

1.2. Research Objectives and Questions

This research aims to explore the current landscape of AI applications in environmental sustainability within the medical and tech industry. By analyzing existing methods, challenges, and emerging trends, this study seeks to identify best practices and strategies for maximizing AI's potential in reducing environmental footprints and advancing towards carbon neutrality. More than a technological tool, AI represents a paradigm shift towards holistic sustainable practices, integrating advanced data analytics and decision-making processes to drive environmentally responsible outcomes.

The main objective of the proposed research thesis is to identify what are the current trends, approaches and methodologies involved in the use and application of AI to achieve environmental sustainability by the medical/healthcare sector and technological industries. In order to better understand AI and all its associated technologies, this research will present a thorough analysis of the history, evolution, definitions, concepts, ethics involved, regulatory frameworks and provide a connection with the industry and organizations which currently act on this state-of-the-art field of work.

Building on this foundation, the second objective is to offer new perspectives to fellow technologic entities which still do not use AI in order to achieve better results on carbon footprints and environmental impacts, filling in existing gaps in academic literature regarding a clear path and usability of novel sources of technology, for more efficient and sustainable management practices in terms of use of products, materials, waste management, energy expenditure and GHGs emissions. Therefore, this dissertation, will try to answer the following 3 questions:

→ Research Question 1: What is AI and how can it be efficiently and safely used?

→ Research Question 2: What is the AI regulatory framework worldwide?

→ Research Question 3: What is the current situation of medical and tech companies regarding their capabilities, applications, data collection and processing methods, support services aimed at environmental sustainability, and what are their main challenges and perspectives for the future?

1.3. Research Framework

The research is organized into five main chapters, aiming to provide a succession of definitions and relations which will analyze the current panorama on the use of AI and ML, starting with introductory statement, research objectives and questions on **Chapter 1**.

Followed by **Chapter 2**, for a thorough empiric literature review which contains subsections on AI definitions, concepts, ethics, history and evolution along the last decades since its origin, connections with the SDGs, an overview of the national, European and international regulatory framework and ending with the analysis of current applications and uses of AI in the sectors of healthcare and technology, as well as the current known AI-based environmental sustainability solutions.

Chapter 3 provides a comprehensive overview of the thesis study methodology, including the research design, the methods used for data collection and analysis, adding to the research survey which was created using *Qualtrics Survey Software* and sent to industry specialists currently acting on this niche field of work on AI-based environmental sustainability solutions.

Chapter 4 then provides a summary exposition of the findings made through the research survey, focusing on the solutions which are currently being applied by the industry professional leveraging AI in environmental sustainability, as well as an in-depth analysis of the data obtained from the survey.

Lastly, **Chapter 5** serves to summarize significant findings and provide conclusions obtained from this study, also detailing the research limitations encountered and a framework of future opportunities for the use of AI for sustainability, suggesting potential directions for further research.

This investigation is particularly timely as organizations worldwide seek to balance technological advancement with environmental responsibility, making the integration of AI in sustainability practices not just an opportunity, but an imperative for future development worldwide. The diagram in Figure 1 below provides a simplified, yet useful, diagram of all the different sectors, resources, factors, communities and the interconnectedness between the key actors in AI, society and the environment, thus representing a brief vision of what this research thesis aims to investigate and analyze for the upcoming chapters.

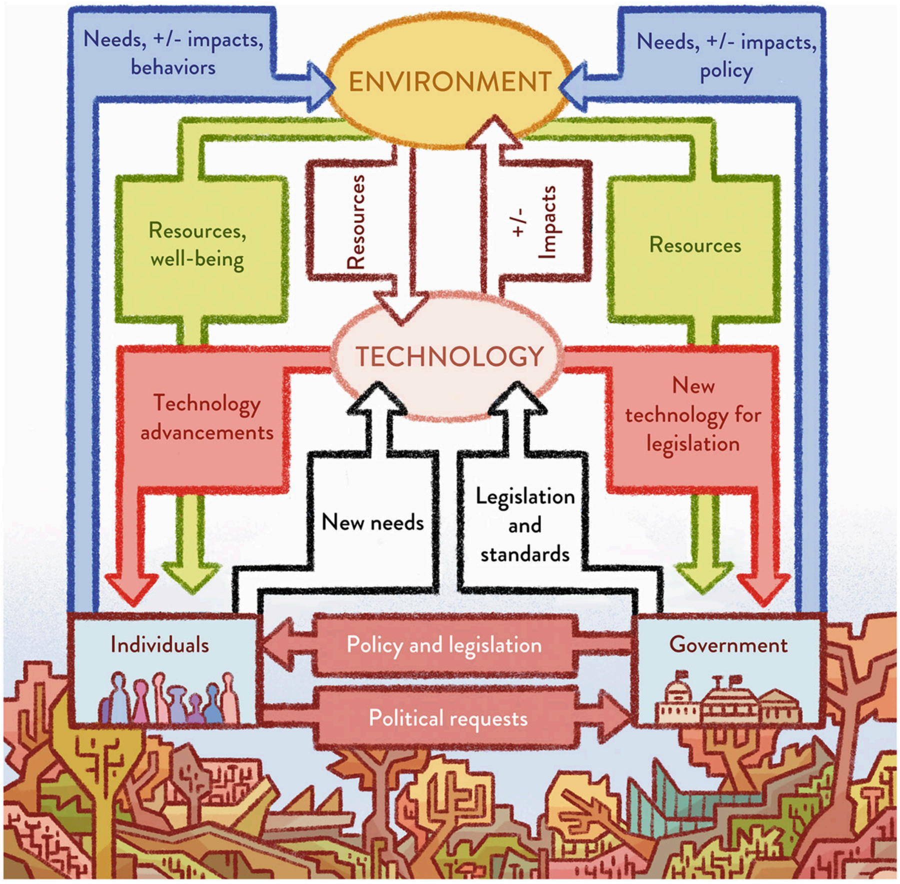

Figure 1 Interaction between AI, society and environment. (Source: Palomares et al., 2021)

CHAPTER 2

Literature Review

Chapter 2 presents a comprehensive review of AI and its intersection with environmental sustainability. Beginning in section 2.1 with the examination of AI fundamentals, including definitions, ethical considerations, historical evolution and connections to the SDGs., then progresses through section 2.2 for analysis of regulatory frameworks. The final section 2.3 examines practical AI applications in the healthcare and technology sectors, culminating in an analysis of AI-based environmental sustainability solutions. This review establishes the theoretical and practical foundation necessary for understanding the research methodology and results presented in subsequent chapters.

2.1. Artificial Intelligence

2.1.1. Definition, Ethics and Fundamentals

AI refers to computer systems which can perform tasks that typically require human intelligence. These tasks include visual perception, speech recognition, decision-making, language translation, and problem-solving (Lecun et al., 2015). The field of AI aims to create machines that can perceive their environment, learn from experience, adapt to new situations, and perform goal-oriented tasks with minimal human intervention.

John McCarthy – often referred to as the father of AI – defined it in 1956 as "*the science and engineering of making intelligent machines*" (McCarthy, 2007). This definition laid the groundwork for future developments in the field. Over time, the definition has expanded to encompass a broader range of capabilities and applications. A more contemporary definition by Russell and Norvig describes AI as the study of agents that receive percepts from the environment and perform actions (Russell & Norvig, 2022). This definition emphasizes the interactive and adaptive nature of AI systems, highlighting their ability to perceive, reason, and act autonomously.

The fundamentals of AI can be broken down into several key components (Russell & Norvig, 2022):

→ <u>Knowledge Representation</u>: This involves encoding information about the world in a form that computer systems can utilize. It includes techniques such as semantic networks, ontologies, frames, and probabilistic models. Effective knowledge representation is crucial for AI systems to reason about complex problems and make informed decisions.

→ <u>Reasoning</u>: AI systems employ various reasoning methods to draw inferences from available knowledge. Including deductive reasoning (drawing conclusions from general principles), inductive reasoning (inferring general rules from specific observations), and abductive reasoning (inferring the most likely explanation for an observation). Advanced reasoning capabilities enable AI to handle complex problem-solving tasks and make logical deductions.

→ Machine Learning: Subset of AI that focuses on algorithms that improve their performance on a specific task through experience. ML includes supervised learning (learning from labeled data), unsupervised learning (finding patterns in unlabeled data), and reinforcement learning (learning through interaction with an environment). Deep learning (DL), a subset of ML based on artificial neural networks, has led to significant breakthroughs in various AI applications.

→ Natural Language Processing (NLP): AI interacting between computers and humans using natural language, including tasks such as language understanding, generation and translation. Recent advances in NLP, led to significant improvements in machine translation, question-answering systems and conversational AI.

→ Computer Vision: Enables machines to gain high-level understanding from digital images or videos, including tasks such as image recognition, object detection and scene reconstruction, being applied in autonomous vehicles, medical imaging and facial recognition systems.

→ Problem Solving: AI systems use various search and optimization algorithms to find solutions to complex problems. This includes techniques such as heuristic search, constraint satisfaction, and planning algorithms. Problem-solving capabilities are crucial for applications like game-playing AI, logistics optimization, and automated planning systems.

→ Robotics: While not all AI systems are embodied, robotics represents an important area where AI algorithms are applied to control physical systems that interact with the real world. This includes aspects like motion planning, object manipulation, and sensory processing.

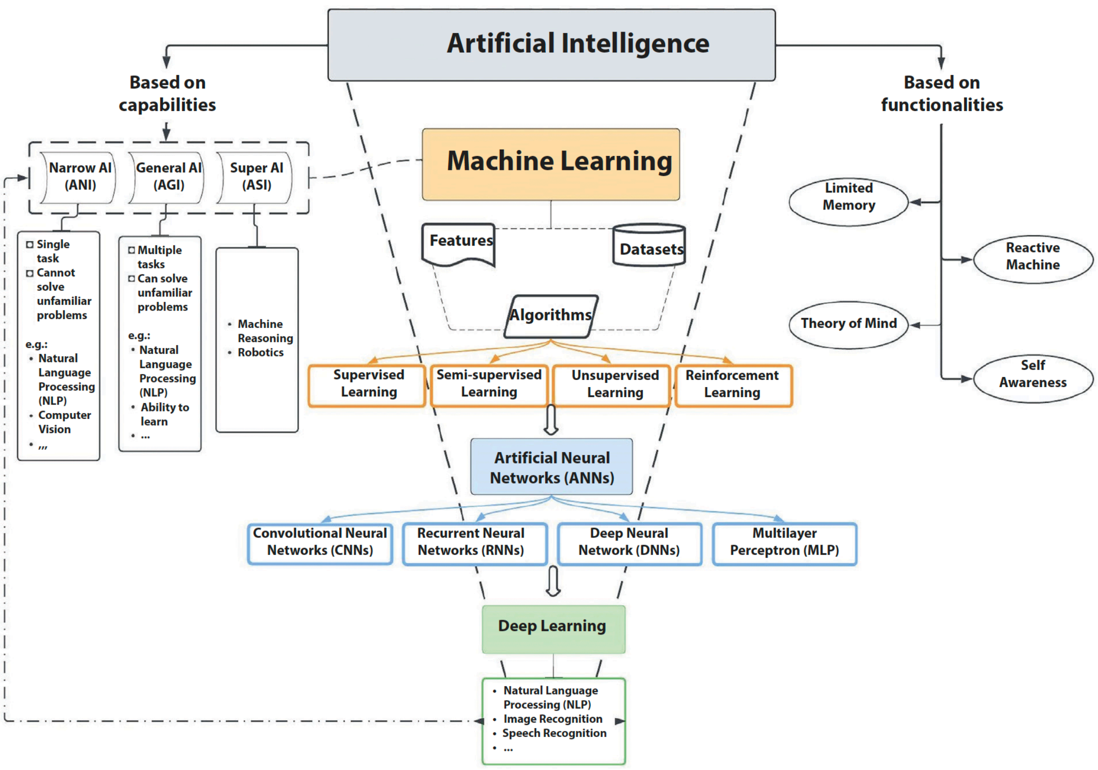

Figure 2 Diagram representing the relationships between AI, ML, and DL. (Source: Bellini et al., 2022)

As we can see from Figure 2 above, all these components work in an intertwined manner, presenting the different AI technologies and their subdivisions under a web-like form. As AI systems become more prevalent and influential, ensuring their ethical development and use has become a critical concern. Scholars have summarized the requirements for AI trustworthiness and safety such as Díaz-Rodríguez et al. (2023), seen below on Figure 3. Several key ethical principles for AI have emerged from guidelines worldwide, such as (Floridi et al., 2018; Jobin et al., 2019):

1. <u>Transparency and Explainability:</u> AI systems should be designed and implemented in ways that allow for scrutiny and understanding of their decision-making processes. This principle is crucial for building trust in AI systems and enabling meaningful human oversight.

2. <u>Justice and Fairness:</u> AI should be developed and used in ways that do not discriminate or perpetuate biases. This includes ensuring diverse and representative training data and implementing fairness constraints in AI algorithms.

3. <u>Non-maleficence:</u> AI should not be designed to harm humans and should incorporate safeguards against potential misuse. This principle extends to considering unintended consequences and potential dual-use applications of AI technologies.

4. <u>Responsibility and Accountability:</u> Clear frameworks should exist for determining responsibility for AI actions and decisions. This includes establishing mechanisms for redress when AI systems cause harm and ensuring human oversight in critical decision-making processes.

5. <u>Privacy and Data Governance:</u> AI systems must respect user privacy and adhere to data protection regulations. This involves implementing privacy-preserving techniques in AI algorithms and ensuring responsible data collection and management practices.

6. <u>Beneficence:</u> The development of AI should be oriented towards benefiting humanity. This principle encourages the use of AI to address global challenges and improve quality of life, while considering potential negative impacts.

7. <u>Human Autonomy:</u> AI should respect human autonomy and not influence or manipulate human decision-making. This principle is particularly relevant in the context of AI-powered recommendation systems and decision support tools.

8. <u>Sustainability:</u> AI development and deployment should consider environmental impacts and contribute to sustainable development goals. This includes optimizing AI systems for energy efficiency and using AI to address environmental challenges.

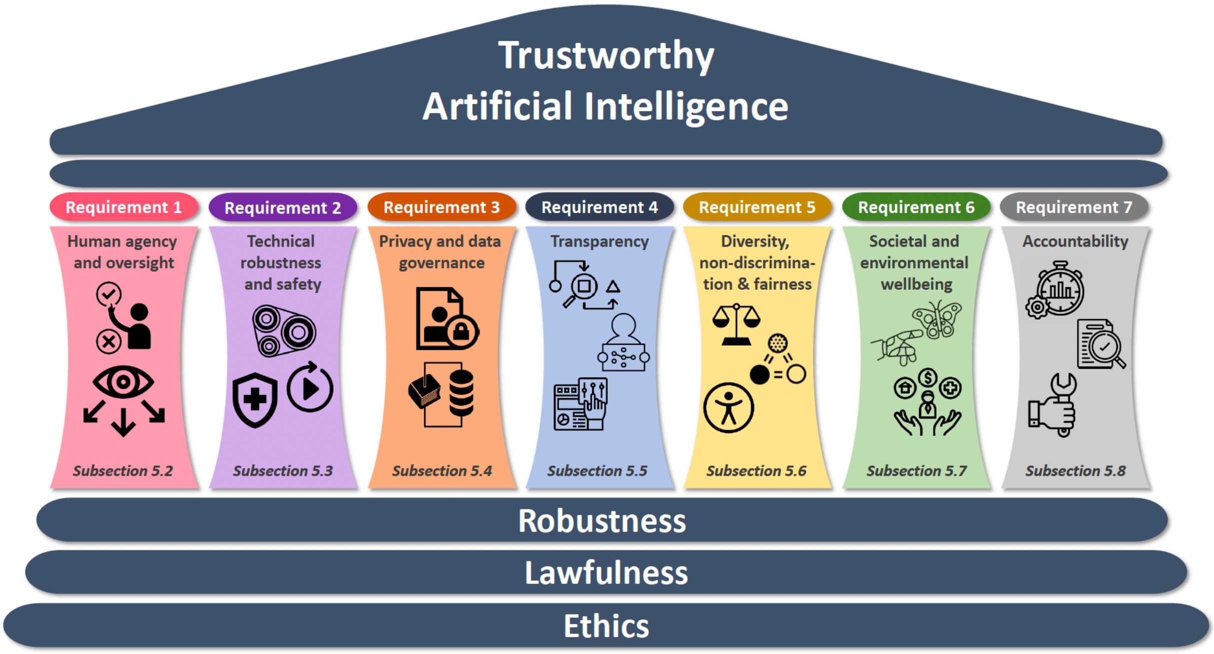

Figure 3 Pillars and requirements of Trustworthy AI. (Source: Díaz-Rodríguez et al., 2023)

These ethical considerations are increasingly being incorporated into AI governance frameworks and guidelines by governments, organizations, and companies worldwide (Zeng et al., 2019). For example, the European Union (EU) has proposed AI regulations that classify AI systems based on their potential risk and impose stricter requirements on high-risk applications (European Commission, 2021). This risk-based approach aims to ensure that AI applications with significant potential impact on individuals or society are subject to appropriate safeguards and oversight.

The integration of these ethical principles into AI development poses both challenges and opportunities. It requires interdisciplinary collaboration between AI researchers, ethicists, policymakers, and domain experts to ensure that AI systems are not only technically robust but also aligned with human values and societal norms (Vayena et al., 2018). This collaboration is essential for addressing complex ethical dilemmas that may arise in AI applications, such as balancing privacy concerns with the potential benefits of data-driven healthcare.

AI affects almost all internationally recognized human rights, directly or indirectly, due to the way they are interrelated and interdependent. **Annex A** shows which human rights – retrieved from the *Articles of the Universal Declaration of Human Rights* – are vulnerable to some AI systems which were already created, produced or designed.

2.1.2. History and Evolution

The history of AI is characterized by periods of rapid advancement, setbacks and paradigm shifts. This section outlines key milestones in AI's evolution. Figure 4 below presents a summarized timeline of AI's main historic events since 1950 until the present day.

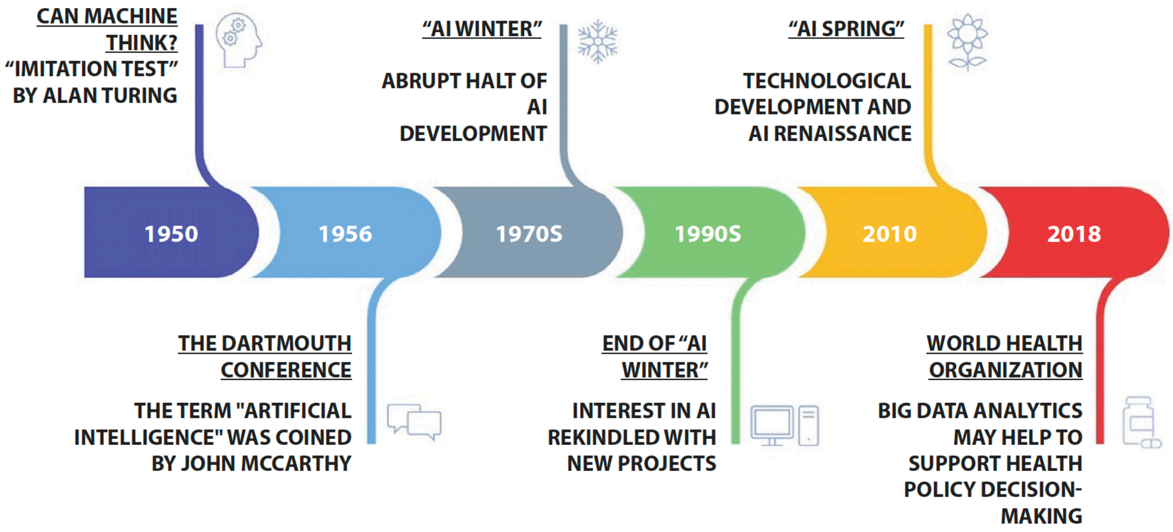

Figure 4 Timeline diagram showing the history of artificial intelligence. (Source: Bellini et al., 2022)

AI history and evolution along the decades can be explained through several milestones (Kaplan & Haenlein, 2019; Lecun et al., 2015; Russell & Norvig, 2022) presented below.

The conceptual foundations of AI can be traced back to the 1940s and 1950s. In 1943, Warren McCulloch and Walter Pitts proposed a model of artificial neurons, laying the groundwork for neural networks. This was followed by Donald Hebb's work in 1949, which suggested a mechanism for learning in biological neurons, later known as Hebbian learning. Alan Turing's paper "*Computing Machinery and Intelligence*" (published in 1950) introduced the Turing Test as a measure of machine intelligence, sparking debates about machine cognition that continue to this day. In the same year, Claude Shannon published a paper on programming a computer to play chess, one of the first instances of game-playing AI.

From 1956 to 1974, the field of AI was officially born at a conference at Dartmouth College (1956), organized by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon. This conference marked the coining of the term "*Artificial Intelligence*". The years following the conference saw rapid progress, with John McCarthy developing the LISP programming language in 1958, and with Arthur Samuel in 1959 developing a checkers-playing program that could learn from experience. In the 60s, work on NLP began, with projects like ELIZA by Joseph Weizenbaum. This period of optimism led to bold predictions about the future of AI, with some researchers suggesting that human-level AI was just around the corner.

From 1974 to 1980, despite early progress, AI faced its first major setback in the 70s. Researchers encountered unexpected difficulties and limitations. The combinatorial explosion problem made many AI algorithms impractical for solving real-world problems. Limitations in computer hardware (HW) restricted the capabilities of AI systems. Many early successes didn't scale up to more complex problems. These challenges led to reduced funding or interest in AI, a period referred as "AI winter".

From 1980 to 1987, saw a resurgence of AI with the rise of expert systems. These were AI programs that emulated the decision-making ability of human experts in specific domains. Notable examples included MYCIN for diagnosing blood infections and DENDRAL for identifying chemical compounds.

From 1987 to 1993, the limitations of expert systems (such as their inability to learn or adapt) and the failure of the *Fifth Generation Computer Project* led to another period of reduced funding and interest in AI. This second "AI winter" was characterized by a shift away from AI-specific HW and programming languages.

From 1993 to 2011, a shift came towards ML approaches. This was driven by improvements in computer HW, the increasing availability of digital data and the development of new algorithms, such as support vector machines and random forests. During this period, AI began to be used in logistics, data mining, medical diagnosis, amongst other areas. The field also saw significant advances in probabilistic reasoning and Bayesian networks.

From 2011 to the present, the era of AI is currently characterized by the success of DL techniques, particularly in areas such as computer vision and NLP. This has been enabled by big data, powerful processing units, and algorithmic innovations. Key milestones including, the deep neural network (*AlexNet*) achieving breakthrough results in the ImageNet competition in 2012, significantly outperforming traditional computer vision techniques. Adding to DeepMind's *AlphaGo* defeating world champion Lee Sedol at the game of *Go* in 2016, a feat previously thought to be decades away. Recent years have seen the development of large language models like GPT-3, also demonstrating impressive natural language abilities.

As AI continues to evolve for the future, research is focusing on several key areas, such as Artificial General Intelligence (AGI), which is the pursuit that AI systems that can perform any intellectual task of a human. Explainable AI, with the development of AI systems that can explain their decisions in ways humans can understand, and last but not the least, AI safety, to ensure that AI systems behave safely and align with human values and species protection.

As AI continues to evolve, interdisciplinary collaborations and innovations will shape its trajectory, paving the way for intelligent systems that enhance human capabilities and drive societal progress. By navigating through historical milestones, AI has emerged as a cornerstone of modern innovation reflecting its transformative impact on technology and society, while promising further advancements in the quest for intelligent systems and autonomous agents.

2.1.3. AI and the Sustainable Development Goals

The intersection of AI and the SDGs has become a critical area of research and policy discussion. The United Nations' 17 SDGs – available in **Annex B** – established in the *2030 Agenda for Sustainable Development*, provide a comprehensive framework for addressing global challenges (UN General Assembly, 2015). As AI technologies continue to advance rapidly, understanding their potential impacts on these goals is crucial for ensuring that technological progress aligns with sustainable development objectives.

A landmark study by Vinuesa et al. (2020) conducted a systematic assessment of AI's potential effects on all 169 targets across the 17 SDGs. Their findings revealed a complex landscape of both opportunities and challenges. The study identified that AI could act as an enabler for 134 targets (79%) across all SDGs, demonstrating the technology's vast potential to contribute positively to sustainable development. However, it also shows that AI could potentially inhibit 59 targets (35%), evidencing the need for careful consideration of AI's implementation and thorough governance.

To provide a structured analysis, Vinuesa et al. (2020) categorized the SDGs into three main groups: **Society**, **Economy**, and **Environment**. This classification allows for a more nuanced understanding of AI's varied impacts across different domains of sustainable development.

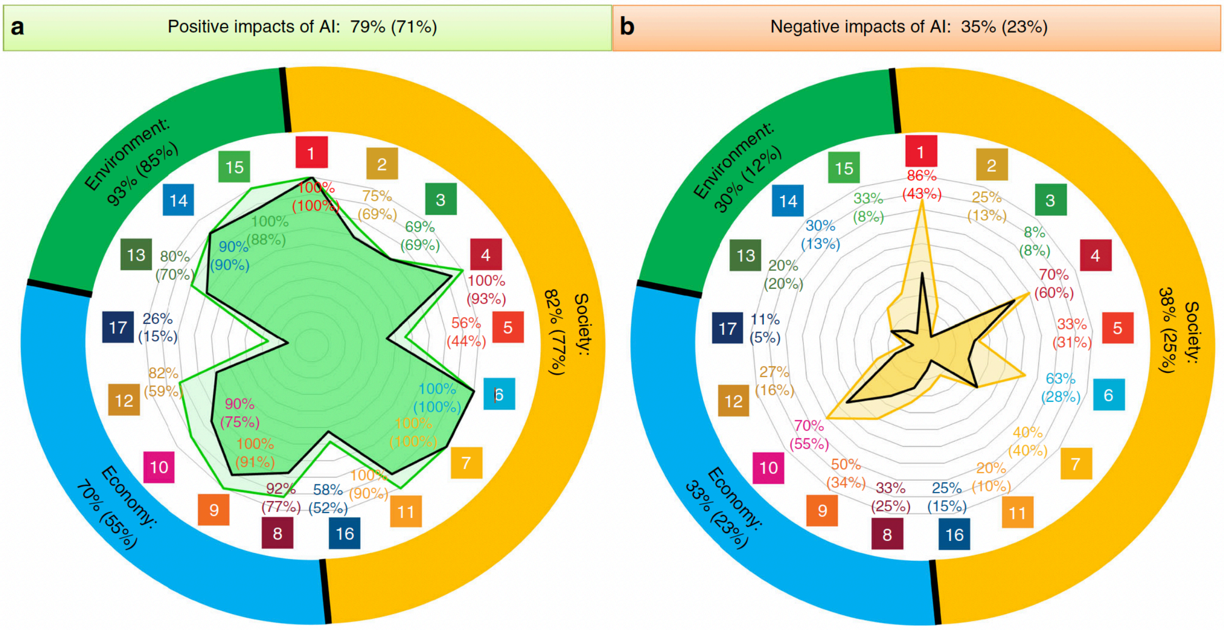

Figure 5 Summary of positive and negative impact of AI on the SDGs. Note: documented evidence of the potential of AI acting as (a) an enabler or (b) an inhibitor on each of the SDGs. The numbers inside the colored squares represent each of the SDGs. The percentages on the top indicate the proportion of all targets potentially affected by AI and the ones in the inner circle of the figure correspond to proportions within each SDG. The results corresponding to the three main groups, namely Society, Economy, and Environment, are also shown in the outer circle of the figure. The results obtained when the type of evidence is taken into account are shown by the inner shaded area and the values in brackets. (Source: Vinuesa et al., 2020)

In the **Society** group, which includes goals related to poverty, hunger, health, education, and gender equality, AI was found to potentially enable 82% of targets. In education (SDG 4), AI-powered personalized learning systems and intelligent tutoring can enhance access to quality education. However, the study also cautioned that AI could exacerbate existing inequalities if not implemented thoughtfully, particularly in areas with limited access to technology or in contexts where AI systems might perpetuate societal biases.

The **Economy** group, encompassing goals related to decent work, economic growth, industry, and innovation, showed that AI could positively impact 70% of targets. AI technologies have the potential to drive productivity gains, foster innovation, and create new economic opportunities. However, Vinuesa et al. (2020) also highlighted risks such as job displacement and the potential widening of economic disparities between and within countries due to uneven access to AI technologies and the skills required to leverage them.

For the **Environment** group, which includes climate action, life below water, and life on land, AI showed the highest potential as an enabler, affecting 93% of targets positively. This aligns with findings from Hannan et al. (2021), who conducted a focused analysis on the role of renewable energy and AI applications in achieving the SDGs. Their study found that renewable energy positively impacted 75 targets (44.3%) across SDGs, while AI applications in renewable energy systems could enable 42 targets (25%).

Specific environmental applications of AI highlighted by both studies state (Hannan et al., 2021; Vinuesa et al., 2020) that AI, and in particularly ML, can enhance climate models, improving our understanding of climate change dynamics and potential impacts. Adding to the optimization of renewable energy systems, with AI significantly improving the integration and efficiency of renewable energy sources. For instance, AI algorithms can optimize the operation of smart grids, balancing supply and demand in real-time and facilitating higher penetration of variable renewable energy sources.

Also evidenced that environmental monitoring, where AI combined with satellite imagery and remote sensing can monitor deforestation, land use changes, and biodiversity loss at unprecedented scales. Water resource management through AI applications, obtaining improved forecasting of water availability, optimization of distribution systems, and early detection of water quality issues. Lastly, sustainable urban planning, contributing to the development of smart cities by optimizing energy use, transportation systems and waste management.

However, both studies also emphasize the potential negative impacts of AI on environmental sustainability. A key concern is the energy-intensive nature of AI systems, particularly large-scale data centers and the training of complex ML models. If not powered by renewable energy sources, the growing energy demand from AI could potentially undermine efforts to reduce GHGs emissions. The rapid pace of AI development and its wide-ranging impacts necessitate careful governance and policy frameworks. It stresses the importance of regulatory insight and oversight to ensure AI development aligns with SDG achievement. This includes addressing issues of transparency, accountability, and ethical considerations in AI systems (Hannan et al., 2021; Vinuesa et al., 2020).

Complementing these findings, a study by Palomares et al., 2021 provides a comprehensive analysis of how renewable energy utilization, including AI-based applications, can impact the achievement of SDGs. Please verify these findings on **Annex C** where the recommendations on using AI in the different SDGs dimensions are listed.

Their research corroborates many of the findings from Vinuesa et al. (2020) and Hannan et al. (2021), while also offering additional insights into the role of AI in sustainable energy systems. The research highlights that AI can play a crucial role in enhancing the efficiency and reliability of renewable energy systems. For instance, AI algorithms can improve the accuracy of renewable energy forecasting, crucial for grid stability and energy market operations. They also note AI's potential in optimizing energy storage systems, a key component in managing the variability of renewable energy sources. However, it also emphasizes the need for a holistic approach when implementing AI in sustainable energy systems. They argue that while AI can significantly contribute to achieving SDG 7 (Affordable and Clean Energy), its impacts on other SDGs must also be considered. For example, the materials used in AI HW and the potential job displacements in traditional energy sectors need to be addressed to ensure alignment with broader sustainability goals.

All three studies underline that while AI and related technologies offer significant potential to advance sustainable development, their impacts are not universally positive. The realization of AI's benefits for sustainable development requires careful consideration of potential negative consequences, proactive measures to mitigate risks, and alignment with ethical principles.

In conclusion, the relationship between AI and the SDGs is profound, while AI presents tremendous opportunities to accelerate progress towards the SDGs, particularly in environmental sustainability, it also poses risks that need to be carefully managed. As AI continues to rapidly evolve, ongoing assessment of its implications for sustainable development will be essential. This includes not only technological research but also interdisciplinary studies that consider the broader societal, economic, and environmental impacts of AI. By doing so, we can work towards harnessing the full potential of AI to support the achievement of the SDGs while mitigating potential negative consequences.

2.2. Regulatory Framework and Legislation

2.2.1. National and European Framework

The landscape of AI regulation in Portugal is inextricably linked to the broader European context, reflecting a dynamic interplay between national initiatives and EU-wide directives. This section examines the evolving frameworks at both the Portuguese and European levels, highlighting their connections and unique characteristics.

In Portugal, the government has recognized the transformative potential of AI and has taken proactive steps to foster its development while ensuring responsible and ethical use. The cornerstone of Portugal's AI strategy is the *AI Portugal 2030* initiative, launched in 2019 as part of the broader *INCoDe.2030* program (AI Portugal 2030, 2019). It outlines Portugal's vision for becoming a pioneer in AI education, research, and application. It focuses on five key action areas:

→ Specialization in areas with international impact;

→ Modernization of public administration;

→ Widespread dissemination of AI knowledge;

→ New technological developments;

→ Addressing social challenges associated with AI.

The strategy emphasizes the importance of developing AI systems that are transparent, auditable, ethical, and accountable, highlighting the need for cross-sector collaboration and the integration of AI across various domains, such as healthcare, education and public services. While Portugal has not yet introduced specific AI legislation, it has implemented the EU's *General Data Protection Regulation* (GDPR) through Law No. 58/2019 (Lei n.º 58/2019, 2019). This law provides a framework for data protection that significantly impacts AI systems processing personal data. The implementation of GDPR in Portugal reflects the country's commitment to aligning with EU-wide data protection standards, which are crucial for AI development and deployment.

In the public sector, Portugal has shown initiative in exploring AI applications. The *Administrative Modernization Agency* (AMA) has played a pivotal role in this effort, developing comprehensive guidelines for responsible AI use in public administration (AMA, 2021). This guideline, titled "*Guia para uma Inteligência Artificial Ética, Transparente e Responsável*" provides a framework for public entities to develop and deploy AI systems responsibly, denoting Portugal's commitment to leveraging AI for public good while maintaining ethical standards and transparency.

On a national level, the set of laws, directives, regulations, measures and principles that preserve government data and digital services that guarantee adequate protection of citizens' personal information are shown in **Annex D** (AMA, 2021).

Portugal's approach to AI also places strong emphasis on research, innovation and skills development. The country has established AI research laboratories and is actively participating in international research collaborations. The *Foundation for Science and Technology* (FCT) has been instrumental in funding AI-related research projects and promoting collaboration between academia and industry (AI Portugal 2030, 2019). Furthermore, recognizing the importance of AI skills for future competitiveness, Portugal has been focusing on education and training initiatives at various levels, from primary schools to universities and professional training programs. Portugal has been actively participating in EU-wide AI initiatives and international forums on AI governance. This includes involvement in the development of Digital Innovation Hubs and participation in EU-level discussions on AI regulation (AI Portugal 2030, 2019; EC, 2021).

To compare Portugal's readiness with the rest of the world, Figure 6 below shows Portugal's positioning in worldwide AI indexes representing the intersection of two indicators for the year 2019:

A. The **AI readiness index**, composed of variables that measure governance, data infrastructure, government and public services, skills, and education in AI;
B. The **global AI index**, composed of variables that measure implementation, innovation, and investment in AI.

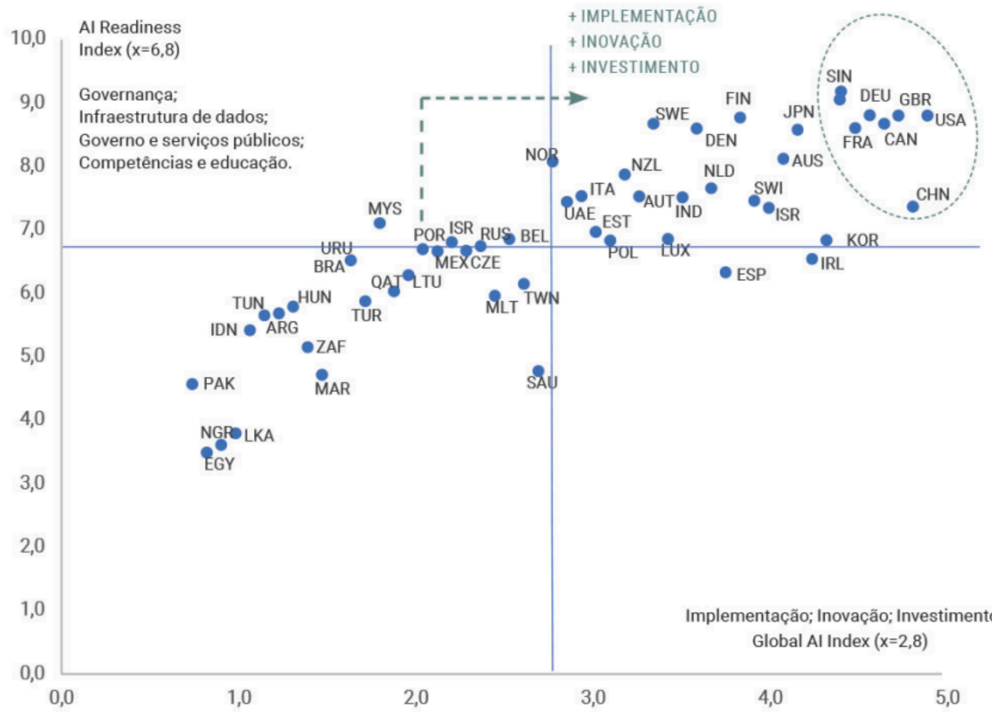

Figure 6 Portugal's positioning in worldwide AI indexes. Note: The countries are positioned in a Cartesian coordinate system, divided into four quadrants by the mean lines of the two indicators. The average of the AI readiness index is 6.8. The average for the global AI index is 2.8 In the 1st quadrant are positioned the countries with indices above the averages of both indicators. In the 2nd quadrant are positioned the countries with values above the average of the AI readiness index, but with values below the average of the global AI index. In the 3rd quadrant, the countries with indices below the averages of both indicators. In the 4th quadrant, the countries with values above the average of the AI readiness index, but with values below the average of the global AI index. (Source: AMA, 2021)

Figure 6 highlights the six countries with the highest AI readiness index and global AI index, which are USA, Germany, UK, Canada, France, and Singapore, as well as Portugal's positioning in this system. Portugal is very close to the average of the AI readiness index, but still below the average of the global AI index, corroborating the need for more implementation, innovation, and investment.

At the European level, the cornerstone of the EU's approach is the proposed AI Act, introduced by the EC in April 2021 (White Paper, 2020). This legislation represents a landmark effort to establish a comprehensive regulatory framework for AI across the EU, being that in December 2023, the European Parliament and Council reached a provisional agreement on the Act, marking a crucial step towards establishing the world's first comprehensive AI law (Council of the EU, 2023). The AI Act adopts a risk-based approach, categorizing AI applications based on their potential harm and imposing corresponding regulatory requirements. It will set a precedent for AI regulation globally and directly affecting all EU member states, including Portugal (Veale & Borgesius, 2021).

This Act aims to establish the world's first comprehensive legal framework for AI, taking a risk-based approach, which are also summarized in Figure 7:

→ Unacceptable risk: Certain AI practices are prohibited, such as social scoring by governments.

→ High-risk: Obligations are imposed on AI systems that impact fundamental rights or safety, adding to requirements for data quality, documentation, human oversight and transparency.

→ Limited risk: Transparency obligations are required for certain AI systems.

→ Minimal risk: Free use of AI is allowed with existing legislation applying.

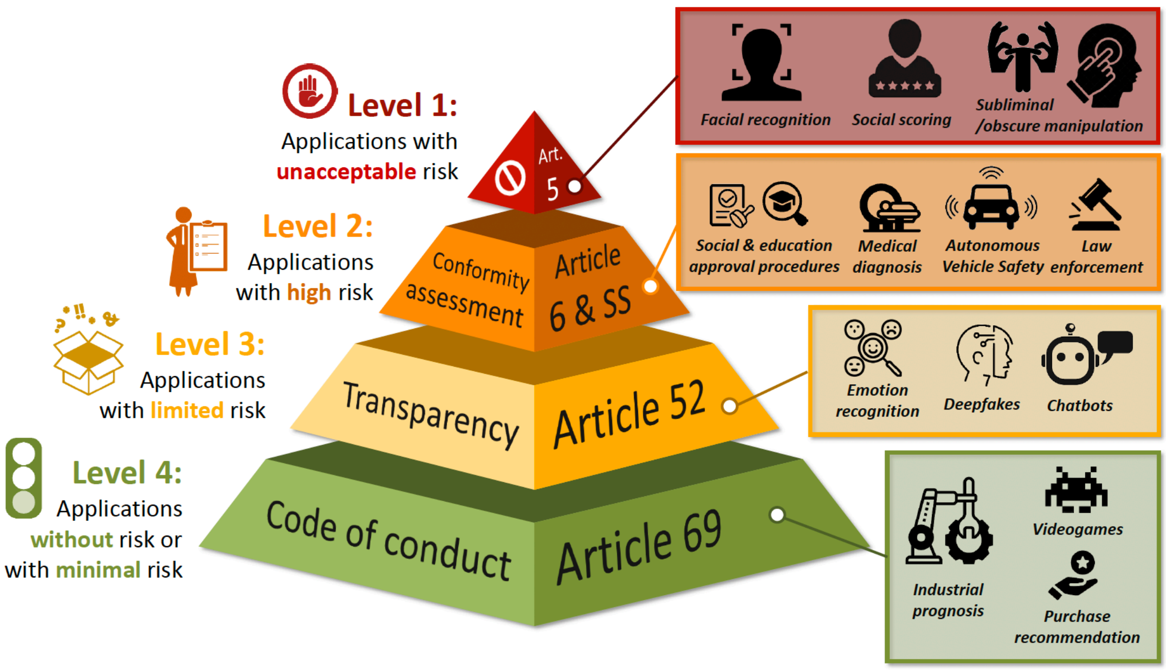

Figure 7 AI Act criticality pyramid and risk-based approach regulatory system for the use of algorithmic systems. Note: Abbreviation "SS" stands for subsequent articles. (Source: Díaz-Rodríguez et al., 2023)

In **Annex E**, we may find the European Legal Framework on AI with all main regulatory milestones listed chronologically. The AI Act entered into force on August 1st of 2024, will become fully applicable 2 years later in 2026, and is expected to have a significant impact on AI development and use across the EU, including in Portugal. The EU has positioned itself at the forefront of AI regulation globally, aiming to foster innovation while safeguarding fundamental rights and ensuring public trust in AI technologies. Complementing the AI Act, the EU has developed a range of initiatives to support AI development and governance. The European strategy for data, unveiled in 2020, aims to create a single European data space, facilitating data sharing across sectors and borders. For instance, in healthcare, there are initiatives to create a European Health Data Space and to regulate AI-based medical devices (White Paper, 2020).

The *Coordinated Plan on Artificial Intelligence* outlines actions for the EU and Member States to strengthen Europe's position in AI development, covering areas such as research funding, skills development and infrastructure creation. The EU has significantly increased funding for AI R&D activities and innovation through programs like *Horizon Europe* and *Digital Europe*, both initiatives aim to boost Europe's AI capabilities and competitiveness (EC, 2021).

Ethical considerations are at the heart of the EU's approach to AI. The *High-Level Expert Group on AI*, established by the EC, published *Ethics Guidelines for Trustworthy AI* in 2019 (Ethics Guidelines of Trustworthy AI, 2019). These guidelines provide a comprehensive framework for ethical AI development, emphasizing principles such as human agency, transparency, and accountability. While continuing to develop its AI policy framework and with more recent initiatives including proposals on AI liability, discussions on the use of AI in law enforcement, and ongoing refinement of the AI Act through the legislative process (EY, 2024; White Paper, 2020).

As an EU member state, Portugal's AI governance approach is significantly influenced by EU-level initiatives. The AI Act, once adopted, will directly be implemented in Portugal, creating a harmonized regulatory environment for AI across the EU. At the same time, Portugal's national initiatives (such as the *AI Portugal 2030* strategy) complement and localize these EU-wide efforts, addressing specific national priorities and challenges. As AI technologies continue to evolve rapidly, EU policymakers face the ongoing challenge of developing governance frameworks that are flexible enough to adapt to new developments while providing clear rules for AI developers and users. The dynamic interaction between national and EU-level regulations will be crucial in shaping a coherent and effective AI governance landscape across the EU.

The *AI Portugal 2030* strategy (AI Portugal 2030, 2019) acknowledges the role of AI in addressing environmental challenges, but while not providing specific regulations, it emphasizes the potential of AI applications in areas such as energy efficiency, smart grids, and environmental monitoring. Portugal's *National Energy and Climate Plan 2030* (PNEC 2030) also mentions the use of digital technologies, including AI, to achieve energy and climate goals. However there is currently no specific regulatory framework in Portugal that directly addresses the environmental impacts of AI or mandates the use of AI for environmental sustainability (Resolução do Conselho de Ministros n.º 53/2020).

The *European Green Deal* is the EU's overarching strategy for sustainable growth, recognizing AI as a key enabler for achieving climate neutrality. The EC's *White Paper* on AI also highlights the potential of AI to address climate change and environmental challenges. More concretely, the proposed AI Act includes environmental well-being as one of the aspects to be considered in the risk assessment of AI systems. While not primarily an environmental regulation, this inclusion demonstrates the EU's recognition of the potential environmental impacts of AI (European Commission, 2019; European Commission, 2021b; White Paper, 2020).

The EU has also introduced initiatives that, while not AI-specific, have implications for the development and use of AI in environmental contexts. For instance, the European Climate Law sets binding targets for climate neutrality, which will likely drive the development and adoption of AI solutions for climate mitigation and adaptation. Similarly, the EU Taxonomy Regulation establishes a classification system for environmentally sustainable economic activities, which could influence the development of AI systems in various sectors. Furthermore, the EU's Digital Strategy emphasizes the need to make the information and communications technologies sector, including AI, more environmentally sustainable. This includes initiatives to improve the energy efficiency of data centers and AI algorithms, addressing concerns about the carbon footprint of AI training and deployment (Regulation (EU) 2020/852, 2020; Regulation (EU) 2021/1119, 2021; EC, 2020).

It's worth noting that while these frameworks provide a foundation for considering the environmental aspects of AI, there is still a need for more specific regulations that address the unique challenges and opportunities at the intersection of AI and environmental sustainability. As both AI technology and environmental challenges evolve, we can expect further regulatory developments in this area at an European level, as well as an international level, which we'll detail further in the following section.

2.2.2. International Framework

The international landscape for AI regulation is intrinsically linked with global efforts to address environmental sustainability. This intersection reflects the growing recognition of AI's potential to both contribute to (and potentially hinder) sustainable development. This section examines the key international initiatives and frameworks that influence AI governance globally, with a particular focus on their connection to environmental sustainability legislation.

At the forefront of international AI governance efforts is the *Organisation for Economic Co-operation and Development* (OECD). In 2019, the OECD adopted the *Principles on Artificial Intelligence* (OECD, 2019), the first intergovernmental standard on AI. These principles promote AI that is innovative, trustworthy, and respectful of human rights and democratic values. Notably, they emphasize "*inclusive growth, sustainable development and well-being*" as a key principle, explicitly linking AI development to environmental and sustainability concerns. Building on the OECD principles, the G20 adopted the AI Principles in 2019 (G20, 2019), extending this framework to major economies outside the OECD membership. The G20 has also recognized the role of AI in addressing climate change and promoting environmental sustainability, as evidenced by discussions in their *Digital Economy Task Force* (G20 Digital Economy Task Force, 2020).

The United Nations (UN) has been active in addressing both AI governance and environmental sustainability. UNESCO's *Recommendation on the Ethics of Artificial Intelligence* (UNESCO, 2021), adopted in 2021, provides a comprehensive framework that explicitly includes environmental considerations. It calls for AI systems to be used to protect the environment and tackle climate change, while also emphasizing the need to assess the environmental impact of AI technologies themselves.

In the realm of climate change, the *Paris Agreement* (UNFCC, 2016) does not explicitly mention AI, but it sets goals that AI can significantly contribute to achieving. For instance, AI can enhance climate modeling, optimize energy systems, and improve climate change mitigation and adaptation strategies. The *UN Environment Programme* (UNEP) has also explored the potential of AI in environmental protection and climate action (UNEP, 2019).

International standardization bodies are playing a crucial role in developing technical standards for AI, including those related to environmental impacts. The *International Organization for Standardization* (ISO) and the *International Electrotechnical Commission* (IEC) have established a joint technical committee on AI (ISO/IEC JTC 1/SC 42). This committee is working on standards for AI technologies, including those related to environmental impact assessment of AI systems. The *IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems* (IEEE, 2019) has produced the ethically aligned design guidelines, which include considerations of environmental sustainability in AI development and deployment.

The *World Economic Forum* (WEF) has been active in shaping international discourse on both AI governance and environmental sustainability. Through initiatives like the *Global AI Action Alliance* (WEF, 2021) and the Center for the 4th Industrial Revolution (WEF, 2024), the WEF is working to accelerate the adoption of inclusive, transparent, and environmentally sustainable AI worldwide. In the specific domain of AI and climate change, initiatives like *Climate Change AI* (Peter Clutton-Brock et al., 2021), an international organization of volunteers from academia and industry, are working to catalyze impactful work at the intersection of climate change and ML, presenting a thorough and comprehensive list of recommendations for governments which we'll analyze further ahead.

The 2024 EY Report titled "*The Artificial Intelligence (AI) global regulatory landscape: Policy trends and considerations to build confidence in AI*" reveals that jurisdictions are adopting a dual approach to AI regulation, encompassing both cross-sectoral and sector-specific strategies. The cross-sectoral approach establishes a foundational framework of essential safeguards applicable across all sectors involved in AI development or implementation. Complementing this, the sector-specific approach introduces additional guidelines or obligations tailored to address unique risks and vulnerabilities within particular industries (EY, 2024). Table 1 below provides examples of how some different jurisdictions can follow an approach for sector-agnostic or sector specific policies on AI.

Table 1 Examples of sector-agnostic and sector-specific policies regarding AI.

JURISDICTION	SECTOR-AGNOSTIC POLICY	SECTOR-SPECIFIC POLICY
Canada	Artificial Intelligence and Data Act (part of Bill C-27)	Public sector (e.g., Directive on automated decision making)
China	Ethical norms for new generation AI Administrative measures for generative artificial intelligence services (draft)	Internet information services (e.g., internet information service algorithmic recommendation management provisions) Interim measures for the Management of Generative Artificial Intelligence Services
EU	AI Act	Industrial machinery (e.g., revision of EU Machinery Directive)
Japan	Governance guidelines for implementation of AI principles	Industrial plant safety (e.g., Guidelines on assessment of AI Reliability in the Field of Plant Safety)
Korea	Implementation strategy for trustworthy AI	City infrastructure improvements (e.g., Smart City Act)
Singapore	Model AI Governance Framework	Financial sector (e.g., MAS FEAT principles)
UK	Roadmap to an effective AI assurance ecosystem	Human Resources (e.g., employment practices: monitoring at work draft guidance)
US	Blueprint for an AI Bill of Rights	Medical Devices (e.g., FDA AI/ML action plan)

Source: EY, 2024.

The *Global Reporting Initiative* (GRI) established in 1997 also plays a significant role in the evolution of environmental sustainability regulatory frameworks and legislation at both European and international levels. On a global scale, the GRI standards have been adopted by companies and organizations in over 90 countries (GRI & SASB, 2021). This widespread adoption promotes a consistent approach to reporting environmental impacts, facilitating comparisons across borders and supporting global efforts towards the SDGs (UN, 2021). The GRI reporting framework aligns with international agreements, such as the UN SDGs and the *Paris Agreement* on climate change (GRI, 2020). This alignment strengthens the credibility of corporate sustainability efforts and contributes to global initiatives to mitigate climate change and promote environmental stewardship. The development of international environmental governance frameworks has a long history, with several key milestones such as the ones presented below.

The 1992 *United Nations Conference on Environment and Development* (UNCED) in Rio de Janeiro, Brazil, led to the adoption of *Agenda 21* and the *Rio Declaration on Environment and Development* (UN, 1992). These agreements emphasized sustainable development principles and called for global cooperation to address environmental challenges. The *Convention on Biological Diversity* (CBD), signed at the Rio Earth Summit, aims to conserve biodiversity, ensure sustainable use of biological resources, and promote equitable sharing of benefits from genetic resources among countries (CBD, 1992). The *Kyoto Protocol*, adopted in 1997, established legally binding commitments for developed countries to reduce GHG emissions under the *United Nations Framework Convention on Climate Change* (UNFCCC) (UN, 1997). It introduced mechanisms such as emissions trading and the clean development mechanism to facilitate emission reductions globally.

The *Paris Agreement*, adopted in 2015 under the UNFCCC, sets a global framework to limit global warming to well below 2ºC above pre-industrial levels, with efforts to limit it to 1.5ºC. It included commitments from countries to submit nationally determined contributions outlining their climate action plans, promote climate resilience, and provide financial support to developing countries (UNFCC, 2016).

It's important to note that while there is growing recognition of the links between AI and environmental sustainability at an international level, there is currently no binding international treaty specifically governing this intersection. Instead, the international framework consists of a patchwork of principles, guidelines, and standards that address both AI and environmental concerns, whether in isolation or conjunction. As AI continues to evolve and as the urgency of addressing climate change increases, international cooperation in AI governance and its connection to environmental sustainability is likely to intensify and become more critical. Challenges such as ensuring AI safety, addressing the global implications of powerful AI systems, promoting equitable access to AI benefits, and leveraging AI for environmental protection are inherently ahead for our near future.

2.2.3. Recommendations for Governments

Based on the comprehensive analysis of the literature from Chapter 2 and regulatory frameworks (mostly focused on the literatures of EY, 2024; Peter Clutton-Brock et al., 2021; and Yaakoubi et al., 2024) we may find on the table below a summary of recommendations for governmental bodies to effectively leverage AI for environmental sustainability.

Table 2 Recommendations for governmental bodies to effectively leverage AI for environmental sustainability

RISK-BASED REGULATORY FRAMEWORK
a) High-risk applications: AI systems deployed in critical environmental domains (e.g., energy grid management, pollution monitoring) should be subject to rigorous oversight and compliance requirements
b) Low-risk applications: AI technologies with minimal environmental impact should be afforded greater regulatory flexibility to foster innovation
SECTOR-SPECIFIC GUIDELINE DEVELOPMENT
a) Data center energy optimization protocols leveraging AI
b) AI-enabled waste reduction strategies in healthcare facilities
POLICY INTEGRATION AND HARMONIZATION
a) Updating existing environmental regulations to incorporate AI-specific provisions
b) Developing new policies that explicitly leverage AI capabilities for environmental goals
c) Ensuring alignment between AI governance frameworks and environmental sustainability objectives
DATA ACCESSIBILITY AND SHARING MECHANISMS
a) Create centralized repositories of environmental data
b) Establish data trusts to facilitate secure and ethical data sharing
c) Implement policies mandating the sharing of environmental datasets from private entities, with appropriate safeguards
R&D INVESTMENT
a) Targeted grant programs for academic research in AI for environmental sustainability
b) Funding mechanisms for public-private partnerships in this domain
c) Direct investment in government-led AI projects for environmental monitoring and management
INTERNATIONAL COLLABORATION INITIATIVES
a) Active participation in multilateral initiatives such as the Global Partnership on AI
b) Establishment of bilateral and multilateral agreements for sharing AI technologies and best practices
c) Creation of international working groups focused on standardizing AI approaches for environmental applications
REGULATORY SANDBOXES FOR ENVIRONMENTAL AI APPLICATIONS
a) Allow for real-world testing of AI applications in environmental settings
b) Facilitate rapid iteration and refinement of AI technologies
c) Inform the development of appropriate regulatory frameworks
COMPREHENSIVE IMPACT ASSESSMENT PROTOCOLS
a) Evaluate intended environmental benefits
b) Assess potential unintended consequences
d) Incorporate both quantitative metrics and qualitative assessments
PROMOTION OF GREEN AI PRACTICES
a) Establishing energy efficiency standards for AI systems
b) Providing tax incentives for companies developing and deploying environmentally friendly AI technologies
c) Incorporating AI energy consumption into broader climate change mitigation strategies

Source: Prepared by the author, information based on EY, 2024; Peter Clutton-Brock et al., 2021; and Yaakoubi et al., 2024.

2.3. AI in the Medical and Technological Sectors

2.3.1. Applicability and Usability in Healthcare

The integration of AI in healthcare marks a paradigm shift in medical practice, offering innovative solutions to longstanding challenges in diagnosis, treatment, and patient care. This subsection examines the applications of AI in healthcare, elucidating its potential to revolutionize medical practices and improve patient outcomes.

AI, and in particularly DL algorithms, has demonstrated remarkable proficiency in medical imaging analysis. These systems can analyze complex medical images such as X-rays, MRIs, CT scans, and mammograms with accuracy often rivaling or surpassing human experts (Esteva et al., 2019). For instance, convolutional neural networks have achieved radiologist-level performance in detecting lung nodules from chest X-rays and identifying intracranial hemorrhages in head CT scans. In dermatology, DL models have shown exceptional capability in classifying skin lesions, including melanoma, with an accuracy comparable to board-certified dermatologists. These advancements suggest the potential for AI to augment clinical decision-making and improve early detection of diseases. As noted by Topol (2019), an increasing number of proprietary algorithms for image interpretation have been approved by the FDA in recent years, which was confirmed on FDA's website. According to an update from the 7th of August of 2024, the regulatory body has already authorized 950 AI/ML-enabled medical devices. In Table 3 below you may find included some of the most prominent AI-based medical applications which have been approved in recent years (Benjamens et al., 2020; FDA, 2024; Topol, 2019).

Table 3 Examples of AI-based medical applications FDA-approved.

COMPANY	FDA APPROVAL	INDICATION
EnsoSleep	March of 2017	Diagnosis of sleep disorders
iCAD	August 2018	Breast density via mammography
IDx	April 2018	Diabetic retinopathy diagnosis
Imagen	March 2018	X-ray wrist fracture diagnosis
Arterys	February 2018	Liver and lung cancer (MRI, CT) diagnosis
MaxQ-AI	January 2018	CT brain bleed diagnosis
Alivecor	November 2017	Atrial fibrillation detection via Apple Watch
GE Healthcare	March 2019	AI-powered X-ray device for pneumothorax detection
Smith & Nephew	January 2020	AI-powered 3D surgical planning software for total knee arthroplasty
Zebra Medical	May 2020	HealthCCS for coronary artery calcification scoring
Caption Health	February 2020	AI-guided cardiac ultrasound software
Aidoc	May 2021	AI for flagging and prioritizing incidental pulmonary embolism
Philips	July 2021	Automated 3D left ventricular ejection fraction measurement
Medtronic	January 2023	AI-powered colonoscopy device (GI Genius)

Source: Benjamens et al., 2020; FDA, 2024; Topol, 2019.

AI algorithms can analyze diverse patient data, including genomic information, electronic health records, and real-time physiological data. By identifying subtle patterns and correlations that may elude human observation, these systems can potentially lead to earlier and more accurate diagnoses. For example, ML models have been developed to predict the onset of sepsis in intensive care unit patient hours before clinical recognition, enabling early intervention and potentially saving lives (Esteva et al., 2019).

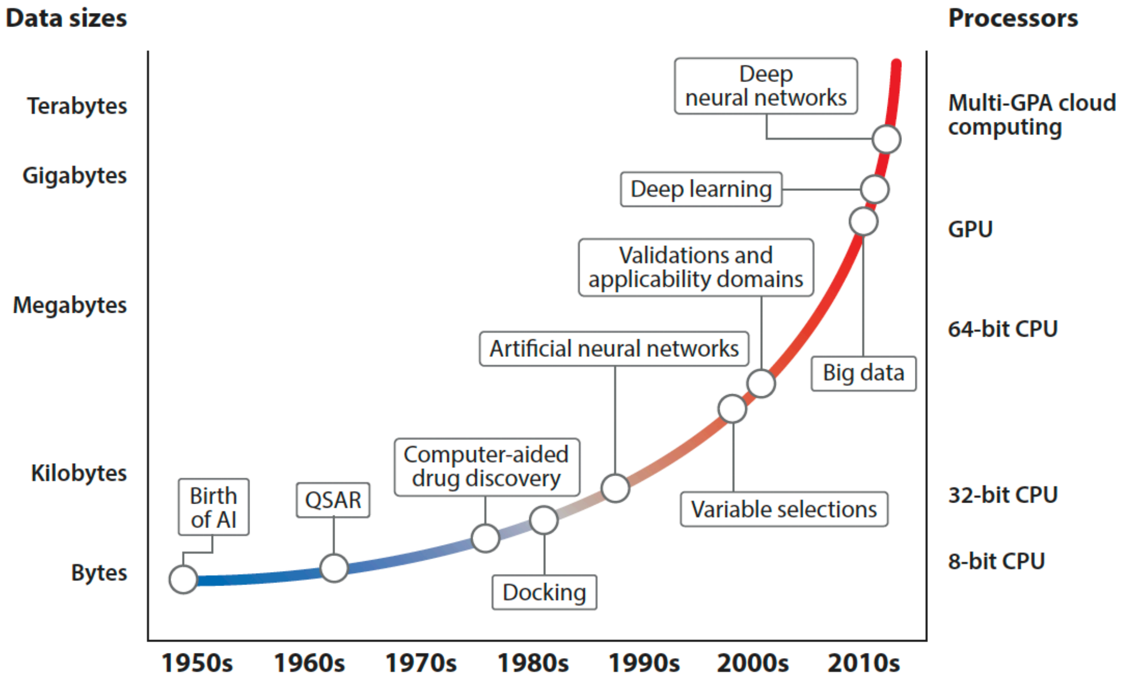

Figure 8 The historical progress of AI in drug discovery coupled with increasing data size and computer power shown as processor improvement. (Source: Zhu, 2019)

The pharmaceutical industry is leveraging AI to revolutionize the drug discovery process, traditionally known for its time-consuming and costly nature. Zhu (2019) details AI applications in this domain, which encompass:

→ Virtual screening of large compound libraries to identify potential drug candidates;

→ Prediction of drug-target interactions and potential side effects;

→ De novo design of novel molecules with specific therapeutic properties;

→ Optimization of lead compounds to enhance efficacy and reduce toxicity.

These AI-driven approaches have the potential to significantly accelerate the drug discovery pipeline and reduce the astronomical costs associated with bringing new drugs to market, as we can see from Figure 8 above. For example, AI algorithms have been used to identify potential treatments for COVID-19 by repurposing existing drugs, demonstrating the technology's ability to respond rapidly to emerging health crises. In one instance, an AI system identified a rheumatoid arthritis drug as a potential treatment for COVID-19 in just three days, a process that would typically take months or years using traditional methods (Zhu, 2019).

AI-powered clinical decision support systems (CDSS) are being integrated into healthcare workflows to assist clinicians in making evidence-based decisions. These systems can analyze patient data from electronic health records to provide real-time alerts and recommendations, suggest appropriate diagnostic tests based on patient symptoms and history, recommend treatment options based on the latest clinical guidelines and patient-specific factors and lastly, predict potential complications or adverse events, allowing for proactive interventions. A notable example is the application of AI in antibiotic stewardship. AI-based CDSS have been shown to improve the appropriateness of antimicrobial prescriptions by suggesting optimal treatments based on local resistance patterns and patient-specific factors. In one study, the implementation of an AI-powered CDSS led to a 32% reduction in broad-spectrum antibiotic use without negatively impacting patient outcomes (Davenport & Kalakota, 2019).

The proliferation of wearable devices and IoT sensors has enabled continuous remote monitoring of patients, generating vast amounts of real-time health data. AI algorithms can analyze this streaming data to detect early signs of health deterioration in chronic disease patients, predicting and preventing acute events such as heart attacks or strokes, monitoring medication adherence and provide personalized reminders, as well as assess mental health status through analysis of speech patterns and social media activity (Topol, 2019). During the COVID-19 pandemic, AI-enabled remote monitoring solutions have been crucial in managing patients at home and reducing the burden on healthcare facilities. For instance, ML models have been developed to predict the likelihood of COVID-19 patients requiring intensive care based on vital signs and laboratory results, enabling more efficient resource allocation and improving patient outcomes (Topol, 2019).

AI is playing a pivotal role in advancing personalized medicine by analyzing large-scale genomic, proteomic, and clinical data to identify biomarkers and genetic variations associated with disease risk and treatment response. This enables for more precise diagnosis and disease subtyping, prediction of individual patient responses to specific treatments, identification of patients at high risk for certain diseases allowing for targeted preventive interventions and for the optimization of drug dosages based on individual patient characteristics (Schork, 2019).

In oncology, AI algorithms are being used to analyze tumor genomic profiles and predict which patients are likely to respond to specific immunotherapies or targeted therapies. For example, a DL model developed by researchers at Stanford University demonstrated the ability to predict patient response to immune checkpoint inhibitors with higher accuracy than existing biomarkers, potentially improving treatment selection and patient outcomes in cancer care (Schork, 2019).

AI is being deployed to streamline administrative processes and improve operational efficiency in healthcare organizations. Applications include (Davenport & Kalakota, 2019) the use NLP for automating medical coding and billing, using chatbots for patient triage and appointment scheduling, predictive analytics for hospital resource management and staff scheduling and lastly, fraud detection in insurance claims processing. By automating routine tasks, AI can reduce administrative burdens on healthcare professionals, allowing them to focus more on patient care. E.g., AI-powered voice recognition and NLP systems can automatically generate clinical notes from doctor-patient conversations, saving time and improving documentation accuracy. Implementing such systems can reduce documentation time by 45% while improving the quality and completeness of the notes (Davenport & Kalakota, 2019).

Regarding healthcare delivery and patient outcomes, Chan and Petrikat (2023) emphasize that AI can enhance operational efficiency and reduce medical errors, while improve patient outcomes across various healthcare domains. They note that AI applications range from medical imaging and diagnosis to drug discovery, clinical decision support, and personalized medicine, reinforcing the potential applications discussed earlier in this section.

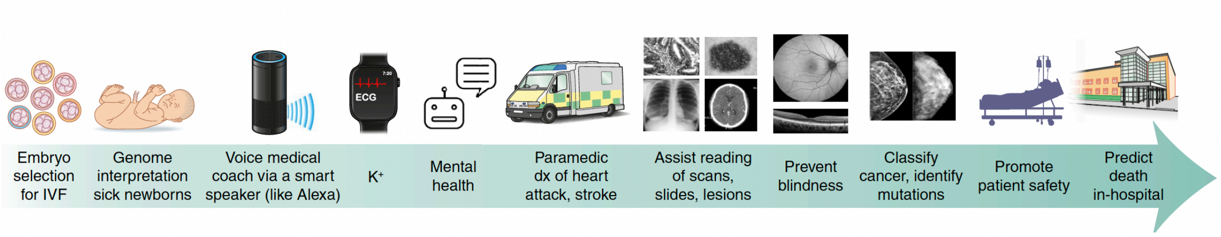

Figure 9 Examples of AI applications across the human lifespan. Diagnosis (dx); In vitro fertilization (IVF); Potassium blood level (K^+). Credit: Debbie Maizels/Spring Nature. (Source: Topol, 2019)

The applications of AI in healthcare are rapidly expanding, offering the potential to revolutionize healthcare delivery across the spectrum from prevention to diagnosis, treatment, and follow-up care, as shown in the Figure 9. As AI tech continues to advance and integrate more deeply into healthcare systems, they promise to enhance clinical decision-making, improve patient outcomes, increase operational efficiency, and ultimately transform the healthcare landscape. However, as Topol (2019) and Vayena et al. (2018) argue, realizing this potential will require addressing significant technical, ethical, and regulatory challenges to ensure the responsible and equitable implementation of AI.

2.3.2. Applicability and Usability in Tech

The integration of AI into various technological domains has ushered in a new era of innovation and efficiency across multiple sectors. As AI continues to evolve, its applicability and usability in technology have expanded exponentially, transforming traditional processes and opening new frontiers of possibility. This subsection delves into specific areas where AI is making significant impacts in the technologic fields and explores the current state of the art.

AI has significantly transformed SW development processes. Amershi et al. (2019) conducted a comprehensive study on AI-assisted SW engineering at *Microsoft*, revealing that AI tools can enhance developer productivity by up to 30% through automating repetitive tasks and providing intelligent code suggestions. Their study identified key challenges in AI-assisted development, including the need for explainable AI and managing the trade-off between automation and developer control.

In HW design and manufacturing, AI plays a crucial role in optimizing processes and improving efficiency. Mirhoseini et al. (2021) showcased the application of deep reinforcement learning for chip floorplanning, achieving superior results compared to human experts in significantly less time. Their AI system, trained on a dataset of 10 000 chip designs, consistently outperformed human experts, reducing floorplanning time from months to hours and improving power, performance, and area metrics by up to 15%. (Wang et al., 2018) also reviewed various DL applications for smart manufacturing, including predictive maintenance, quality inspection and process optimization. They found that convolutional neural networks and long short-term memory networks were particularly effective in defect detection and time series prediction tasks, respectively, with some implementations achieving over 95% accuracy in fault diagnosis.

AI has become indispensable in managing data centers and cloud computing resources, Gao (2014) reported on *Google*'s use of AI to optimize data center operations, particularly focusing on cooling efficiency. By applying ML algorithms to the massive amounts of data collected from sensors throughout their data centers, *Google* was able to reduce the amount of energy used for cooling by up to 40%. The AI system, developed in collaboration with DeepMind, used neural networks to predict future temperature and pressure conditions in the data center, allowing for proactive adjustments to cooling systems. This approach not only significantly reduced energy consumption but also improved the overall stability of the data center environment.

Adding to Chenhau et al. (2016) which developed a deep reinforcement learning-based resource management system for cloud computing that dynamically allocates computing resources, their system improved resource utilization by 20 to 30% and reduced service level agreement violations by up to 50% compared to static allocation methods.

In network management and telecommunication, AI enables predictive maintenance, network traffic optimization, and enhanced security measures. Chen et al. (2017) provided a comprehensive tutorial on ML applications in wireless networks, covering topics such as resource allocation, network security and mobility management, denoting how DL models could improve sensing accuracy by 30% and reduce energy consumption in 5G networks by 70% through intelligent sleep mode scheduling. Consumer electronics have been also significantly enhanced by AI, from personalized user experiences to optimized device performance, where Marikyan et al. (2019) reviewed AI's role in smart home applications, finding that AI-powered systems could reduce energy consumption by 10 to 25% through intelligent thermostat control and appliance management.

In the context of manufacturing, Huang et al. (2021) discussed how AI-driven Digital Twins (DT) can optimize resource utilization and reduce waste generated by up to 30%, contributing to more sustainable production and manufacturing processes. Table 4 below showcases the different applications where methods of AI integration in DT are applied in manufacturing lines (most specifically in the fields of production planning and control, quality control and logistics), while Figure 10 represents a visual example of a DT in manufacturing.

Table 4 Examples of AI-enabled DT applications in smart manufacturing.

FIELD	AI-CATEGORY	APPLICATION-CASE
Production Planning	Supervised Learning	1. Material or tool holder selection 2. Tool wear level prediction
	Reinforcement Learning	1. Dynamic scheduling of flexible manufacturing systems
	Computational Intelligence	1. Optimization of production scheduling 2. Optimization of smart assembly lines 3. Scheduling optimization of a gear production workshop 4. Design of automatic flow-shop manufacturing system
Production Control	Supervised Learning	1. Resource allocation for sequential manufacturing operations 2. Assembly commissioning process optimization 3. Geometrical quality improvement in assembly
	Reinforcement Learning	1. Box sorting in a material flow control system 2. Optimization of conveyor systems and order dispatching 3. Optimizing order dispatching 4. Human behavior forecasting
Quality Control	Supervised Learning	1. Welding quality prediction (deformation) in an assembly line 2. Anomaly detection of surface deviations of a truck component 3. Feature recognition of parts
Logistics	Computational Intelligence	1. Abnormal condition detection and location information preservation

Source: Huang et al. 2021.

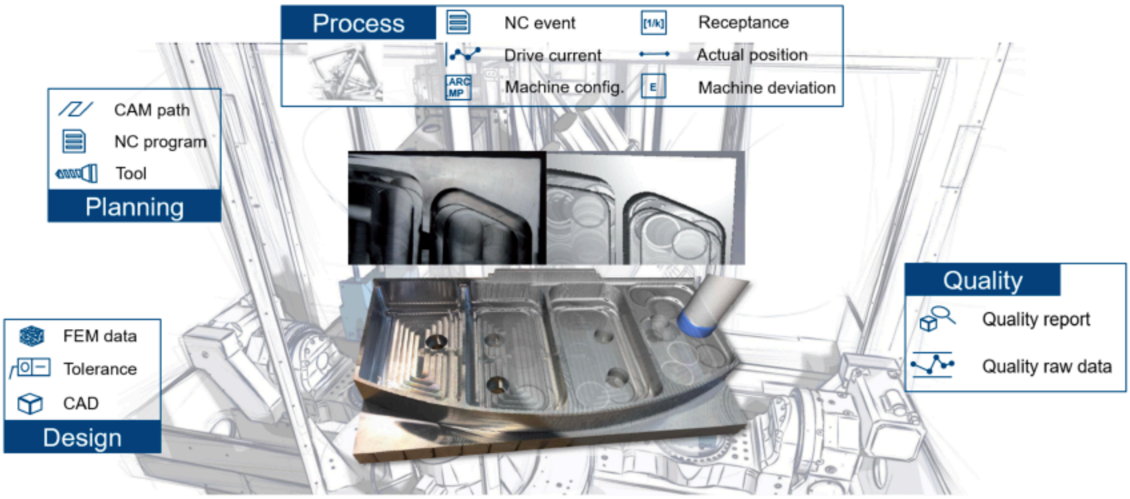

Figure 10 DT illustration in manufacturing: workpiece quality monitor. (Source: Huang et al. 2021)

Looking ahead, emerging trends such as edge AI and quantum computing promise to further revolutionize the tech landscape. Li et al. (2019) reviewed the state-of-the-art in edge AI, discussing its potential to enable faster, more efficient processing in IoT devices. They found that edge AI could reduce latency in IoT applications by up to 80% and improve privacy by keeping sensitive data local. All these trends align with the future directions for AI-driven technology, emphasizing the need for more adaptive, efficient, and transparent AI systems that can operate in real-time manufacturing environments under a safe and effective manner.

2.3.3. AI-based Environmental Sustainability Solutions

The integration of AI in environmental sustainability efforts represents a significant frontier in addressing global ecological challenges. This section explores the all-round applications of AI in promoting environmental sustainability, with practical examples presented. As previously analyzed in section 2.1.1, the widespread adoption of AI raises important challenges and ethical considerations, despite its clear benefits to modern day societies. As an example, Strubell et al. (2019) mentioned the significant environmental impact of training large AI models, estimating that training a single large NLP model can emit as much CO_2 as five cars over their lifetimes.

AI has revolutionized climate change modeling and prediction, enabling the processing of vast amounts of climate data from various sources, including satellite imagery, weather stations, and ocean sensors. DL models, such as those developed by researchers at *DeepMind*, have demonstrated remarkable accuracy in short-term weather prediction and long-term climate modeling (Reichstein et al., 2019). These AI-driven models can identify complex patterns and relationships within climate systems that might be overlooked by traditional statistical methods, leading to more accurate predictions of extreme weather events and long-term climate trends (Huntingford et al., 2019).

AI technologies are instrumental in advancing waste management practices and promoting a circular economy. Computer vision and robotics, powered by AI, are enhancing recycling processes by accurately sorting different types of waste materials. ML algorithms analyze consumption patterns and supply chain data to optimize resource use and minimize waste generation. The *Ellen MacArthur Foundation* has shown how AI can be used to design products for easier disassembly and recycling, a key principle of the circular economy concept, visible in Figure 11 below (Ellen MacArthur Foundation, 2019).

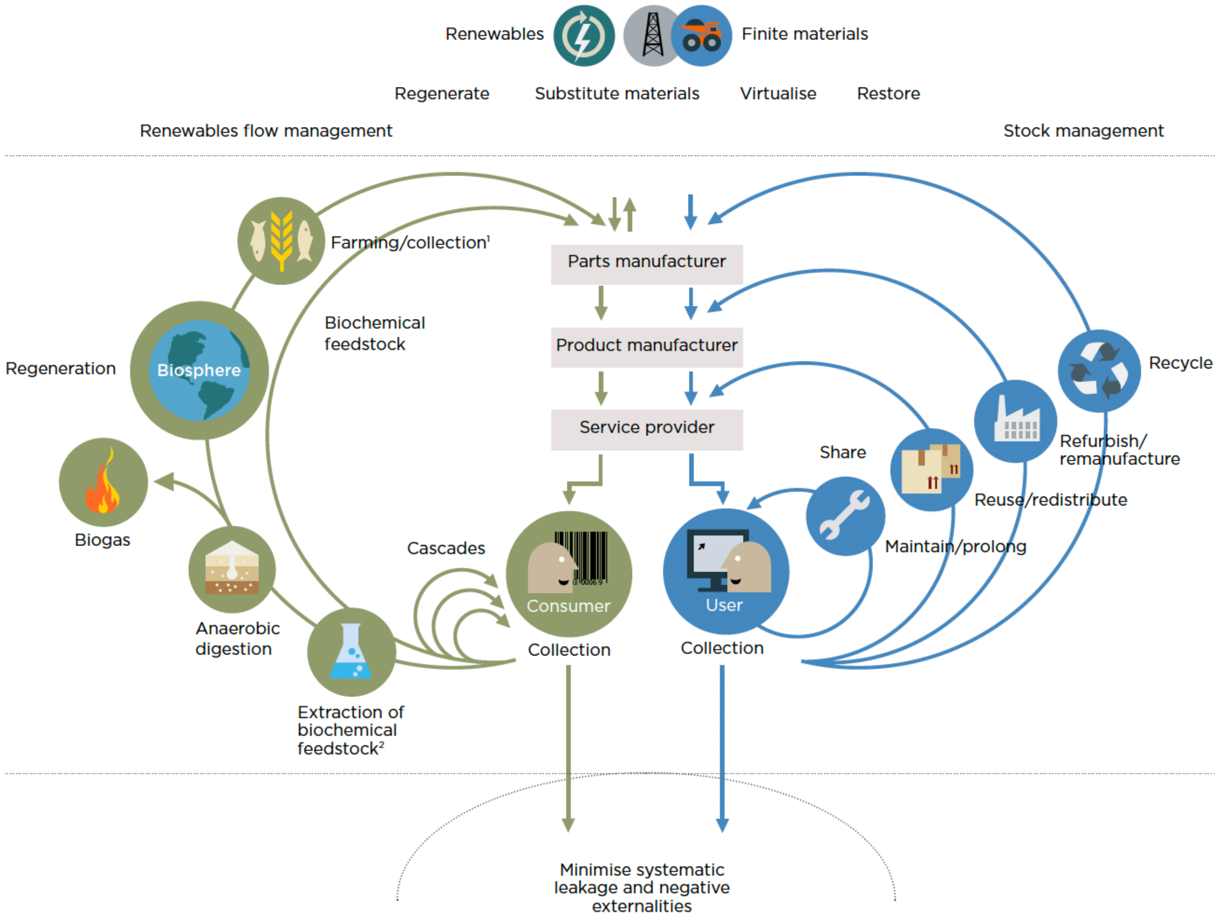

Figure 11 The circular economy system diagram (Source: Ellen MacArthur Foundation, 2019)

AI plays a crucial role in optimizing energy consumption and facilitating the transition to renewable energy sources, where ML algorithms are employed in smart grid systems to predict energy demand, optimize distribution and integrate renewable energy sources more efficiently. For instance, *Google*'s *DeepMind* AI has been used to reduce the energy consumption of data centers by up to 40% (Evans & Gao, 2016). In the realm of renewable energy, AI algorithms optimize the placement and operation of wind turbines and solar panels, maximizing their energy output based on weather patterns and geographical factors.

It is also becoming an invaluable tool in biodiversity conservation efforts. ML models trained on vast datasets of animal images and sounds, can monitor and track wildlife populations more efficiently than traditional methods (Tabak et al., 2019). For instance, the *Rainforest Connection* project uses AI to analyze audio data from rainforests to detect illegal logging activities in real-time (Rainforest Connection, 2019). Similarly, computer vision techniques are employed to identify and count animal species from camera trap images, providing crucial data for conservation efforts (Norouzzadeh et al., 2018). AI technologies are also increasingly used to monitor and protect ocean ecosystems. DL models analyze satellite imagery to track coral reef health, detect illegal fishing activities and monitor ocean pollution (Marre et al., 2019). For instance, the *Allen Coral Atlas* project uses AI to create high-resolution maps of the world's coral reefs, providing vital information for conservation efforts (Allen Coral Atlas, 2021).

In agriculture, AI is driving the development of precision farming techniques that optimize resource use and minimize environmental impact. ML algorithms analyze data from soil sensors, satellite imagery, and weather forecasts to provide farmers with actionable insights on irrigation, fertilization and pest control (Liakos et al., 2018). As an example, the *FarmBeats* project by *Microsoft* uses AI to help farmers increase yields while reducing water and fertilizer use (Microsoft Research, 2021).

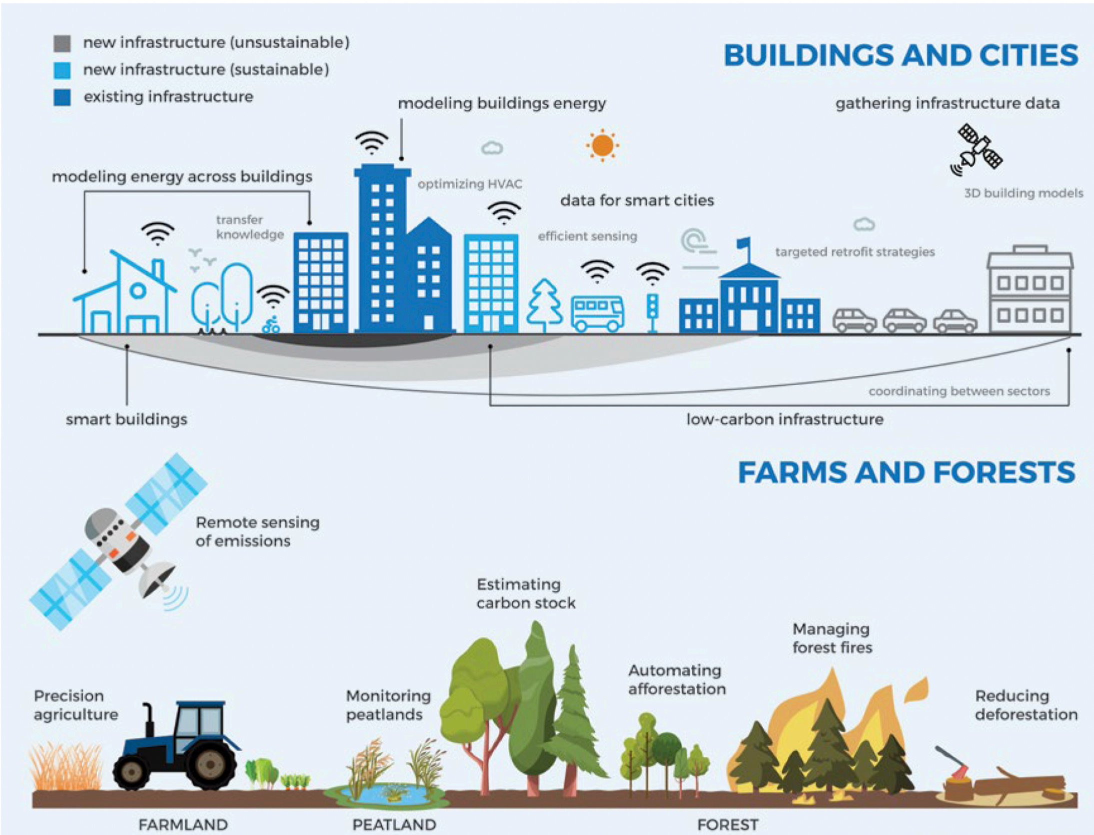

Figure 12 Selected AI-for-climate applications within buildings, cities, farms and forests. (Source: Rolnick et al., 2019)

In monitoring and improving air quality in urban areas, ML models analyze data from air quality sensors, traffic patterns and weather conditions to predict pollution levels and identify sources of emissions (Rybarczyk & Zalakeviciute, 2018). These insights enable city planners to implement targeted interventions to reduce air pollution, contributing to improved public health and environmental quality in urban settings (Bellinger et al., 2017). AI is also instrumental in developing sustainable urban environments, as ML algorithms can optimize traffic flow and reduce congestion and GHGs emissions, being that AI-powered simulations could help urban planners design energy-efficient buildings and green spaces, contributing to more sustainable and livable cities (Bibri & Krogstie, 2017).

AI systems are increasingly used to support environmental policy and decision-making processes. ML models can analyze complex environmental datasets to identify trends and predict the outcomes of different policy scenarios. This can help policymakers make more informed decisions about resource management, conservation efforts and climate change mitigation strategies (Rolnick et al., 2019).

AI's role in environmental sustainability is complex and rapidly evolving – from climate modeling to waste management, AI technologies are providing innovative solutions to pressing environmental challenges. However, realizing the full potential of AI for environmental sustainability will require continued research, interdisciplinary collaboration, and careful consideration of ethical and environmental implications.

Table 5 below has been created to summarize all the different AI-based environmental sustainability solutions which are currently being applied worldwide. These solutions aim to optimize processes, reduce environmental impacts, carbon footprints and enhance sustainability practices across different economic, social and environmental sectors.

Table 5 Summary of AI-based environmental solutions.

1. ENERGY MANAGEMENT & OPTIMIZATION
Energy Consumption: AI to monitor and analyze energy use patterns, identify inefficiencies and suggest improvements. **Predictive Maintenance:** Implementing AI-driven predictive maintenance to foresee equipment failures and optimize the maintenance schedule, thereby improving energy efficiency and reducing downtime.
2. WASTE MANAGEMENT & RECYCLING
Smart Waste: AI for automated waste sorting and classification to enhance recycling efficiency and reduce landfill use. **Waste Reduction:** AI to analyze production processes and identify opportunities to reduce waste generation.
3. SUPPLY CHAIN OPTIMIZATION
Logistics and Transportation: AI to optimize routing and scheduling for transportation and reducing fuel consumption. **Sustainable Sourcing:** AI to assess and monitor the sustainability of supply chains, ensuring that materials and products are sourced responsibly.
4. ENVIRONMENTAL IMPACT ASSESSMENT
Real-time Monitoring: Implementing AI-driven systems to continuously monitor environmental parameters such as air and water quality, and greenhouse gas emissions. **Impact Analysis:** Using AI to model and predict the environmental impact of different operational strategies and scenarios.

5. RESOURCE MANAGEMENT
Water Management: Employing AI to optimize water usage in industrial processes, detect leaks, and improve overall water efficiency. **Material Efficiency:** Using AI to track and optimize the use of raw materials, reducing waste and enhancing material lifecycle management.
6. CARBON FOOTPRINT REDUCTION
Emission Tracking: Implementing AI systems to track and manage carbon emissions across operations. **Carbon Offsetting:** Using AI to identify and manage carbon offset opportunities, such as reforestation projects or renewable energy investments.
7. SUSTAINABLE PRODUCT DESIGN
Eco-friendly Design: Leveraging AI to design products that are more sustainable, using less material and easier to recycle. **Lifecycle Analysis:** Using AI for lifecycle analysis to understand the environmental impact of products from creation to disposal and to improve their sustainability.
8. REGULATORY COMPLIANCE & REPORTING
Compliance Monitoring: Using AI to ensure that operations comply with environmental regulations and standards. **Automated Reporting:** Implementing AI-driven systems for generating detailed and accurate sustainability reports, facilitating transparency and accountability.
9. DATA ANALYTICS & INSIGHTS
Big Data Integration: AI to integrate and analyze large datasets related to environmental sustainability, providing actionable insights and strategic recommendations. **Predictive Analytics:** AI to predict future environmental trends and prepare for regulatory changes, market demands, and sustainability challenges.
10. CONSULTING & ADVISORY SERVICES
Sustainability Strategy Development: Offering expertise to develop comprehensive sustainability strategies that leverage AI for enhanced effectiveness. **Training and Education:** Providing training programs to help clients understand and implement AI-driven sustainability practices.

Source: Prepared by the author.

Several emerging trends were also identified in the application of AI for environmental sustainability, such as the increasing use of edge computing for real-time environmental monitoring and decision-making, as explored by Sayed-Mouchaweh (2020). The novel concept of explainable AI, a growing focus on developing transparent and interpretable AI models for sustainability applications, a trend noted by Arrieta et al. (2020). And lastly, federated learning, which is a technique to address data privacy concerns in collaborative AI projects for sustainability, as discussed by Lim et al. (2019).

Adding to the above-mentioned emerging trends, Table 6 below offers us some real-world cases of AI-based environmental practices being currently used by companies or governments worldwide (Peter Clutton-Brock et al., 2021).

Table 6 AI-based environmental practices case studies.

CASE STUDIES OF AI-BASED ENVIRONMENTAL PRACTICES
Climate TRACE: Uses AI and satellite data to track global GHG emissions with improved accuracy and transparency.
UK National Grid ESO: Uses AI to double the accuracy of electricity demand forecasts, enabling better integration of renewables.
Kuzi: AI tool developed in Kenya to predict locust outbreaks, helping farmers adapt to climate change.
Aionics: Uses AI to accelerate battery design process, providing a 10x speedup in developing better batteries for electric vehicles and grid storage.
Monitoring the Andean Amazon Project: AI and satellite imagery to detect illegal deforestation in the Amazon real-time.
RTE (France's electricity transmission system operator): Leads a competition series called Learning to Run a Power Network (L2RPN) to validate AI algorithms for optimizing power grids.
United Nations Satellite Centre (UNOSAT) FloodAI: Uses AI to deliver high-frequency flood reports based on satellite data, improving disaster response in Asia and Africa.
InFraRed project (Austrian Institute of Technology): Uses AI to model urban microclimates, allowing simulations to run in seconds instead of hours.
Fero Labs: Uses AI to help steel manufacturers reduce the use of mined ingredients, preventing an estimated 450,000 tons of CO2 emissions per year.
Arup Neuron system: Deployed in buildings around Hong Kong, uses AI-based optimization to boost building energy efficiency by 10-30%.
Deutsche Bahn: AI to improve reliability and scheduling in rail transport, detecting failures and maintenance needs early.
AI tools for analyzing climate risk in financial disclosures: Developed by researchers in Canada, Switzerland, and Germany to automatically analyze corporate reports for climate-related risks.
DeepMind: Developed AI algorithms to reduce energy needed for cooling Google's data centers by about 30-40%.

Source: Peter Clutton-Brock et al., 2021.

These AI-driven innovations have significant implications for the industry. For instance, healthcare facilities can leverage AI-optimized energy management systems (e.g. the *Arup Neuron* system), to reduce their carbon footprint while maintaining optimal patient care environments. AI-enhanced supply chain management, following the example of *Deutsche Bahn*'s approach, can help medical device manufacturers and pharmaceutical companies minimize waste and improve logistics efficiency. AI tools can be adopted to analyze climate risk in financial disclosures to assess and report on their environmental impact more accurately. AI-driven battery innovations (such as *Aionics*) can lead to more efficient and sustainable medical devices and equipment. Telehealth platforms can incorporate AI to optimize server usage and reduce energy consumption (e.g. *Google*'s *DeepMind* with data centers as mentioned previously). By embracing AI-based solutions, industries can significantly contribute to their environmental sustainability goals while improving operational efficiency. This synergy between AI and environmental sustainability not only addresses immediate environmental concerns but also sets the stage for a more resilient and eco-friendly future in the modern-day industry.

CHAPTER 3

Methodology

Chapter 3 outlines the research approach and methods employed to investigate AI's role in environmental sustainability within the health and technology industry. It details the research design choices, data collection methods, as well as the survey development process. This chapter explains how the methodology aligns with the research objectives and questions established in Chapter 1, providing transparency about the research process and enabling replication of the thesis study.

3.1. Research Design

The research design employs a mixed-methods approach, combining predetermined and open-ended questions, while using quantitative and qualitative data collection techniques. This methodology was chosen for its flexibility and capacity to gather both quantitative data and qualitative insights, crucial for understanding the complex interplay between AI and environmental sustainability.

The primary data collection instrument is a survey – available in **Annex F** – developed using the online platform *Qualtrics Survey Software*, structured to mirror the depth of a semi-structured interview. This approach allows for a comprehensive exploration of the research questions while accommodating the time constraints of professionals in the health and tech sectors. Ethical considerations, including participant consent and data anonymity, were prioritized in the survey design. To encourage open and honest responses while protecting individual and organizational identities, all responses are anonymized. However, the survey still collects information about generic organizational characteristics and functions to provide context for the analysis.

The research survey is divided into six main sections:

1. <u>Respondent Introduction</u>: This section gathers organizational characteristics, such as company sector, respondent's professional function/position and type of organization.
2. <u>AI Capabilities and Applications</u>: Exploring the specific AI technologies employed within the organization and their applications in environmental sustainability contexts.
3. <u>Data Collection, Analysis, and Results</u>**:** This section investigates how organizations collect, and process data related to sustainability metrics.
4. <u>Client Support and Outcomes</u>: Examines how organizations assist their clients in improving environmental sustainability outcomes using AI-based solutions.
5. <u>Challenges and Future Direction:</u> This section explores the primary challenges in implementing AI-based solutions for environmental sustainability and outlook for the future.
6. <u>Additional Comments</u>: Open-ended section for respondents to provide any additional insights that may be relevant to the questionnaire.

The survey design was informed by both practical industry sources and key theoretical frameworks identified in the literature review. The AI capabilities section reflects the fundamental components outlined by Russell & Norvig, (2022), while the applications section incorporates environmental sustainability use cases documented by Rolnick et al. (2019) amongst others. Questions about implementation challenges and data processing techniques were influenced by regulatory considerations from the EU AI Act and technical implementations discussed by Huang et al. (2021). The outcomes and metrics sections were aligned with sustainability indicators identified in the SDGs framework and case studies from industry leaders.

This dual foundation in both theory and practice enabled the survey to capture a comprehensive view of AI's current and potential role in environmental sustainability in the health and technological industries, enabling a robust analysis of the current state, challenges, and future potential of AI, providing both width and depth in addressing the research questions and objectives presented in this work.

3.2. Data Collection and Survey

The data collection process was conducted through the distribution of the online survey to professionals in relevant positions within organizations operating in the health and tech sectors.

The target respondents included individuals from various organizational types, such as:

→ Technology or IT Services Providers.
→ Healthcare IT or Software Providers.
→ Environmental Consultancy Firms.
→ Medical Device Manufacturers.
→ Pharmaceutical Companies.
→ Biotechnology Firms.
→ Healthcare Providers or Medical Institutions.
→ Research Institutions or Academic Organizations.
→ Government Agencies or Public Sector Organizations.
→ Non-Governmental Organizations (NGOs) or Non-Profit Organizations.

The online questionnaire was designed to take approximately 5 minutes to complete by the respondents, encouraging a higher response rate while still gathering comprehensive data. Participants were assured of the confidentiality of their responses and participation was entirely voluntary. All respondents that participated in the survey were contacted via publicly available company emails, mobile contacts, or directly through the social network platform *LinkedIn.*

The research survey employs multiple measurement approaches to capture both qualitative and quantitative impacts of AI implementation. The effectiveness of AI applications was measured using a five-point Likert scale, ranging from 1 (not at all effective) to 5 (extremely effective), across several dimensions. These dimensions encompass the several AI capabilities, environmental applications and client support services.

To gather concrete quantitative data on environmental impacts, respondents were asked to provide specific percentage-based metrics for various sustainability measures. These include GHGs emissions reduction achieved through AI implementation, waste production reduction rates, renewable energy integration success rates, recycling improvement percentages, community engagement levels and biodiversity conservation metrics. These quantitative measures were designed to capture both the range (minimum to maximum) and average values of achieved improvements, providing tangible benchmarks for AI's environmental impact. This combination of effectiveness ratings and specific performance metrics enables a comprehensive assessment of AI's current impact and future potential in environmental sustainability initiatives.

The methodological approach enables comparison of perceived effectiveness across different AI applications and capabilities, while identifying areas where AI solutions are delivering the strongest environmental benefits. It facilitates understanding of the variance in implementation success across different organizations and allows for basic quantification of concrete environmental improvements achieved through specific AI implementation methods. This adaptable measurement strategy provides the base foundation for detailed analysis of AI's role in driving environmental sustainability within the health and technology industries, while also identifying areas where implementation challenges may be limiting potential benefits.

CHAPTER 4

Results and Analysis

Chapter 4 presents and analyzes the findings from the research survey, examining how organizations currently implement AI for environmental sustainability in the health and tech industries. The analysis progresses from respondent profiles through specific AI capabilities, applications and challenges, ending with future outlooks. Each subsection provides detailed examination of the data, connecting findings to the theoretical framework of the revised literature established in Chapter 2 and addressing the research objectives and questions outlined in Chapter 1.

4.1. Survey Results and Analysis

This section presents a comprehensive analysis of the survey results regarding the role of AI in achieving environmental sustainability within the health and tech industries. The survey gathered a total of 23 responses from a total of 62 companies contacted, representing a 35% response rate, offering valuable insights into the current landscape of AI applications, challenges and prospects.

4.1.1. Overview of Respondents Profile

The survey was answered by a diverse range of participants from organizations within the health and technological industries, however the tech field had most participants, as evidenced in the chart in Figure 13 below.

Answers were received from people operating on the following functions/positions: Sales; Inbound Sales; VP Sales; Data Officer; Data Scientist; Environmental Officer; Founder & CEO; ESG Professional; Company Partner; Carbon Sourcing Manager; Sustainability Analyst; Sustainability Consultant; Head of Product, AI Solutions; Market Trends, Competitive Intelligence.

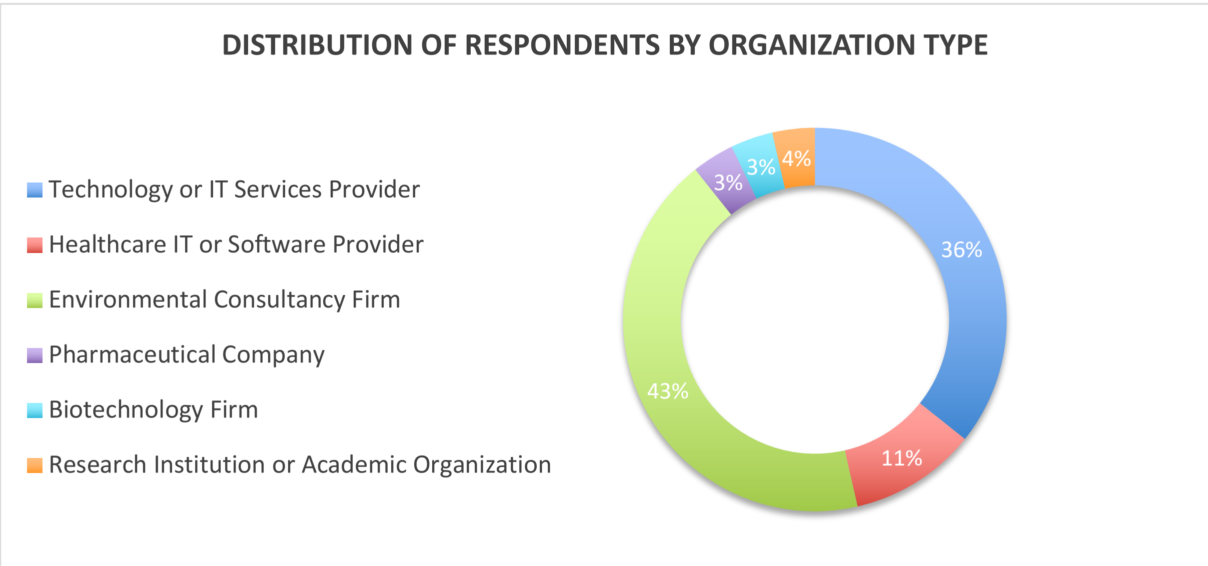

Figure 13 Distribution of respondents by organization type.

The survey captured a diverse range of organizations involved in AI applications for environmental sustainability. The distribution of respondents was as follows:

1. Environmental Consultancy Firms: 43% (12 respondents);
2. Technology or IT Services Providers: 36% (10 respondents);
3. Healthcare IT or Software Providers: 11% (3 respondents);
4. Research Institution or Academic Organization: 4% (1 respondent);
5. Biotechnology Firms: 3% (1 respondent);
6. Pharmaceutical Companies: 3% (1 respondent).

To ensure comprehensive representation, respondents were allowed to select multiple organization types, acknowledging that some categories may overlap or that organizations might have diverse focuses. As a result, the 23 respondents provided a total of 28 selections, indicating the complex nature of some organizations in this field. The analysis in the following sections presents the aggregated findings across all organization types, as detailed cross-sectional analysis would require access to individual response data or could not be accurate, due to the possibility of multiple selection option in organization type in the research survey and to the limited number of answers obtained.

The chart illustrates that environmental consultancy firms and technology companies are at the forefront of applying AI to environmental sustainability challenges. Together, these two categories account for 79% of the respondents, representing their significant role in this field. From the 62 companies contacted, the distribution of responses (and non-responses) reveals notable patterns. Environmental consultancy firms and technology or IT services providers showed the highest engagement rates, together accounting for 79% of responses (43% and 36% respectively). The high response rate from these sectors suggests their advanced involvement and established interest in AI-based environmental sustainability solutions.

Conversely, certain sectors showed lower response rates or did not respond at all. Medical device manufacturers, pharmaceutical companies (only one response), and healthcare providers were among the least responsive segments, despite being part of the target audience. This pattern might indicate either lower current engagement with AI-based environmental solutions in these sectors or different priorities regarding environmental sustainability initiatives. The low response rate from healthcare-focused organizations (11% of total responses) particularly highlights the emerging nature of AI-based environmental sustainability initiatives in this sector.

This response distribution provides valuable context for interpreting the subsequent analysis, suggesting that while AI-based environmental sustainability solutions are well-established in environmental consultancy and technology sectors, they may still be in earlier stages of adoption in healthcare-related industries, or possibly, representing that healthcare-related industries resort to 3rd party services or external suppliers if applying AI technology in environmental sustainability sectors.

4.1.2. AI Capabilities for Environmental Sustainability

Figure 14 below depicts the prevalence of various AI capabilities being leveraged for environmental sustainability solutions among the respondents, being able to select multiple options.

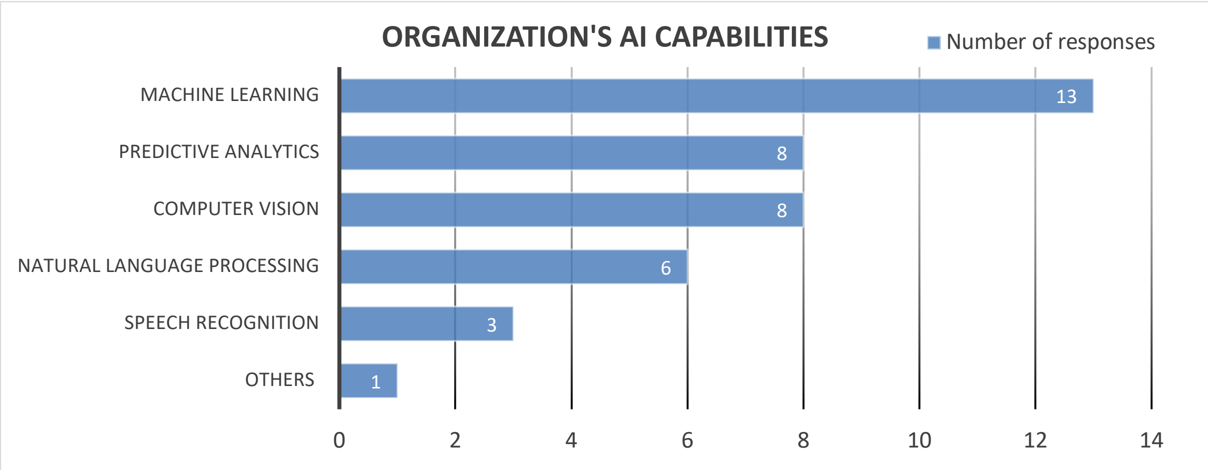

Figure 14 Organization's AI capabilities relevant to environmental sustainability solutions.

Based on the number of responses obtained regarding their AI capabilities:

1. Machine Learning (57%, 13 respondents);
2. Predictive Analytics (35%, 8 respondents);
3. Computer Vision (35%, 8 respondents);
4. Natural Language Processing (26%, 6 respondents);
5. Speech Recognition (13%, 3 respondents);
6. Others (4%, 1 respondent).

In terms of effectiveness, it was also asked in terms of the respondents' perception, how efficient their AI capabilities were in addressing existent environmental sustainability challenges, using a ranking scale from 1 (not at all efficient) to 5 (extremely efficient), as Figure 15 below presents.

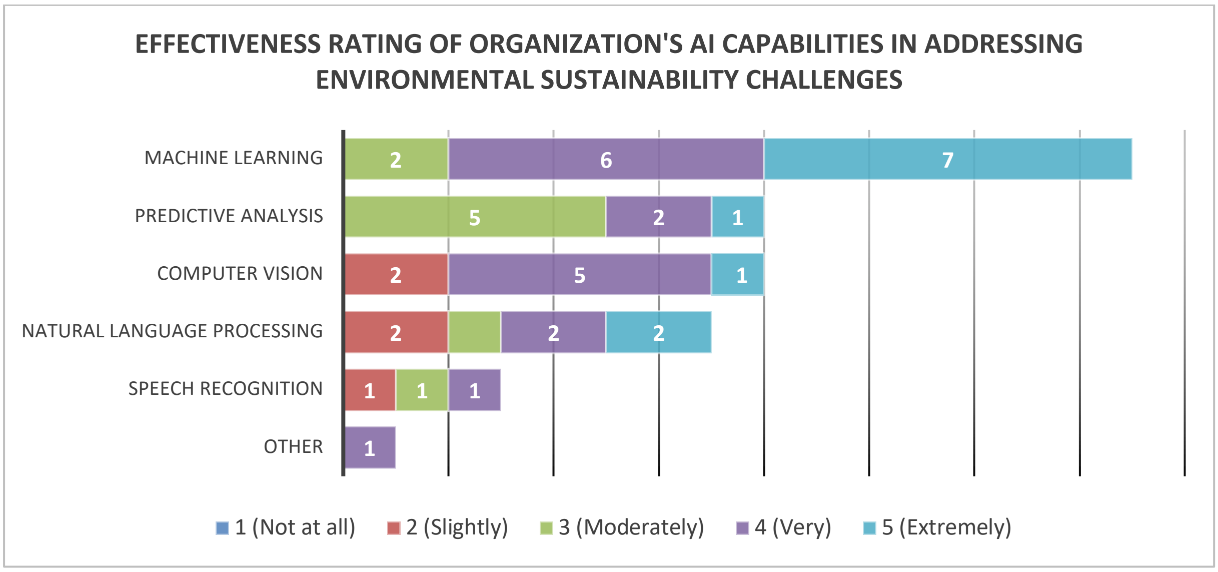

Figure 15 Organization's AI capabilities relevant to environmental sustainability solutions effectiveness ranking.

Machine Learning emerged as the dominant capability, employed by 57% of respondents (13 organizations). The high adoption rate is complemented by its effectiveness rating, averaging 4.2 out of 5, indicating that organizations find ML particularly effective for environmental sustainability applications. This suggests that ML's adaptability and analytical power make it especially suited for addressing complex environmental challenges.

Predictive analytics and computer vision share second place in adoption, each utilized by 35% of organizations (8 respondents). Predictive analytics achieved an average effectiveness rating of 3.8, while computer vision scored 3.6, suggesting both technologies deliver substantial value in their respective applications, being crucial for data-driven forecasting and image-based environmental analysis.

Natural Language Processing is employed by 26% of organizations (6 respondents), with an effectiveness rating of 3.4. While less adopted, organizations using NLP find it valuable for processing and analyzing textual data, though slightly less effective than ML and predictive capabilities.

Speech recognition, while showing limited adoption at 13% (3 respondents), received an effectiveness rating of 3.0, indicating that while useful for specific applications, it may have more limited applicability in environmental sustainability contexts compared to other AI capabilities.

One respondent (4%, 1 organization) indicated "Other" specialized AI capabilities, rating its effectiveness at 4. This suggests the existence of innovative or specialized AI applications in the sustainability field that don't fit into the main categories.

These survey findings strongly align with the theoretical foundations of AI discussed in section 2.1.1, where ML was identified as a core component of modern AI systems. The high adoption rate of ML (57%) among respondents mirrors the literature's emphasis on ML's versatility and effectiveness across various applications. This practical implementation validates the theoretical framework presented by Russell & Norvig (2022), particularly regarding the hierarchy of AI capabilities where ML serves as a foundational technology. The strong presence of predictive analytics and computer vision (both at 35%) in the survey results also reflects the industry applications presented in section 2.3.2, where these technologies were shown as essential for process optimization and quality control in technological sectors.

The effectiveness ratings reported by survey respondents provide empirical validation of the theoretical advantages discussed in the literature review. The high effectiveness rating for ML (4.2 out of 5) particularly corresponds with the successful applications documented under sections 2.3.1 and 2.3.2, where ML-based systems have demonstrated significant impact in both healthcare and tech applications. This alignment between theoretical potential and practical implementation suggests that organizations are successfully translating academic understanding of AI capabilities into real-world environmental sustainability solutions.

4.1.3. AI Applications in Environmental Sustainability

When examining the specific applications of AI in environmental sustainability contexts, several key areas stood out. The horizontal bar chart (Figure 16) below outlines the key AI applications in environmental sustainability, showing the applications where AI has the most significant impact. Once again, respondents were able to select more than one application, for a total of 87 selections made.

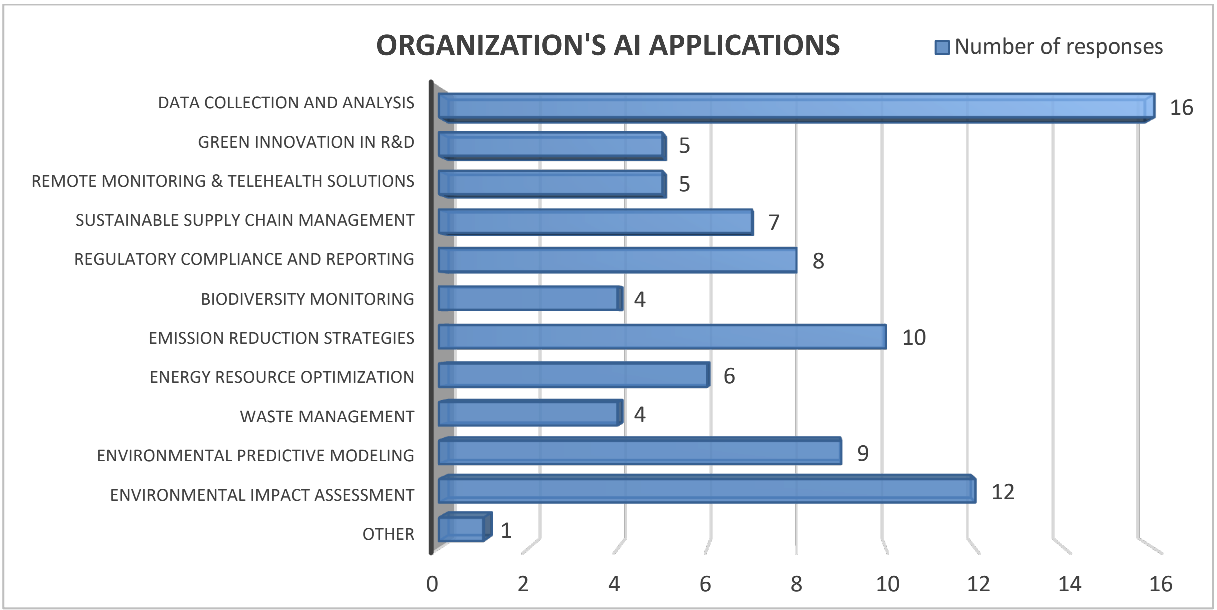

Figure 16 Organization's AI applications in environmental sustainability contexts.

The survey reveals a wide range of AI applications in environmental sustainability, with respondents selecting multiple options. The choice distribution, from most to least used, is as presented here:

1. Data Collection and Analysis (70%, 16 respondents);
2. Environmental Impact Assessment (52%, 12 respondents);
3. Emission Reduction Strategies (43%, 10 respondents);
4. Environmental Predictive Modeling (39%, 9 respondents);
5. Regulatory Compliance and Reporting (35%, 8 respondents);
6. Sustainable Supply Chain Management (30%, 7 respondents);
7. Energy Resource Optimization (26%, 6 respondents);
8. Remote Monitoring & Telehealth Solutions (22%, 5 respondents);
9. Green Innovation in R&D (22%, 5 respondents);
10. Biodiversity Monitoring (17%, 4 respondents);
11. Waste Management (17%, 4 respondents);
12. Other (4%, 1 respondent).

Additionally, it was also asked similarly on the AI capabilities section, for respondents to provide a ranking from 1 to 5, in terms of effectiveness perception of their AI applications in addressing environmental sustainability solutions, coming to the creation of Figure 17 below.

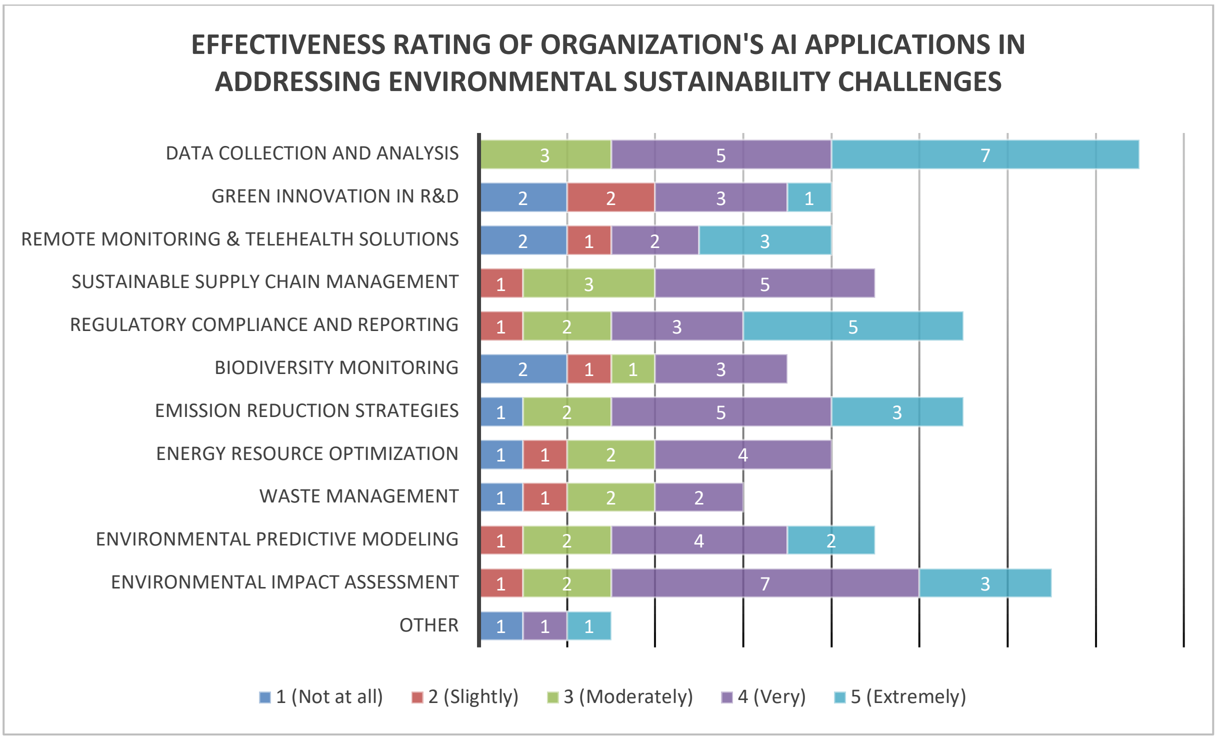

Figure 17 Organization's AI applications in environmental sustainability contexts effectiveness ranking.

The data illustrates a diversified approach to applying AI in environmental sustainability contexts, which is detailed per AI application below.

<u>Data collection and analysis</u> emerged as the predominant application, employed by 70% of respondents (16 organizations) and achieving a noteworthy effectiveness rating of 4.1 out of 5. This high adoption rate coupled with strong effectiveness suggests that organizations find value in AI's capabilities for processing and analyzing environmental data, as a base foundation.

<u>Environmental impact assessment</u> ranked second in adoption (52%, 12 respondents) with an effectiveness rating of 3.8. This substantial uptake indicates organizations' strong focus on quantifying their environmental effects, with AI providing reliable analytical support for these assessments.

<u>Emission reduction strategies</u> showed significant adoption (43%, 10 respondents) and received an effectiveness rating of 3.9, one of the highest among all applications. This high effectiveness score suggests that when implemented, AI solutions are particularly successful in helping organizations achieve their emission reduction goals.

<u>Environmental predictive modeling</u> and <u>regulatory compliance and reporting</u> demonstrated moderate adoption rates (39% and 35% respectively) with effectiveness ratings of 3.7 and 3.5. These ratings indicate that while these applications may be more complex to implement, they deliver meaningful value in supporting environmental planning and compliance requirements.

Sustainable supply chain management (30%) and energy resource optimization (26%) showed lower adoption rates but achieved relatively high effectiveness scores of 3.8 and 4.0 respectively. The high effectiveness rating for energy resource optimization, despite lower adoption, suggests this may be an underutilized application with significant potential for wider implementation.

Applications such as remote monitoring and telehealth solutions and green innovation in R&D (both at 22%) received effectiveness ratings of 3.4 and 3.6 respectively, indicating positive but moderate impact in these specialized areas. The lower adoption rates may reflect the more specific nature of these applications or their emerging status in environmental sustainability contexts.

Biodiversity monitoring and waste management (both at 17%) showed the lowest adoption rates among specified applications, with effectiveness ratings of 3.3 and 3.5 respectively. While these applications demonstrate positive impact when implemented, their lower adoption rates suggest potential opportunities for expansion in these critical environmental areas.

This data reveals several key insights about AI applications in environmental sustainability:

→ High-adoption applications tend to show strong effectiveness ratings, validating organizations' implementation choices.

→ Some lower-adoption applications, particularly energy resource optimization, demonstrate excellent effectiveness, suggesting opportunities for wider deployment.

→ The overall effectiveness ratings (all above 3.0) indicate that AI applications generally meet or exceed expectations across all environmental sustainability contexts.

→ Organizations appear to prioritize applications focused on measurement, analysis, and strategic planning over more specialized operational applications.

The distribution of AI applications revealed by the survey demonstrates remarkable alignment with the potential impacts on SDGs discussed in section 2.1.3. The high adoption rate of data collection and analysis (70%) and environmental impact assessment (52%) directly corresponds to the enabler role of AI identified by Vinuesa et al. (2020) in achieving environmental SDGs. These findings provide empirical validation of the theoretical framework presented in section 2.1.3, where AI was projected to positively impact 93% of environmental targets within the SDGs.

Furthermore, the applications reported in the survey closely mirror the AI-based environmental sustainability solutions detailed in section 2.3.3. The focus on emission reduction strategies (43%) and environmental predictive modeling (39%) aligns with the practical applications discussed in the literature, particularly regarding climate change modeling and environmental monitoring systems. The lower adoption rates in areas such as waste management (17%) and biodiversity monitoring (17%), despite their high effectiveness ratings (3.5 and 3.3 respectively), suggest untapped potential in these areas, confirming the opportunities for expanded implementation identified in the literature review.

4.1.4. Data Collection and Processing Techniques

Efficient data collection and processing are crucial for the successful implementation of AI in environmental sustainability initiatives. The survey also explored the methods applied by organizations to employ their objectives. Figure 18 shows the number of responses on data collection and processing techniques currently used by the respondents on their AI based environmental sustainability solutions.

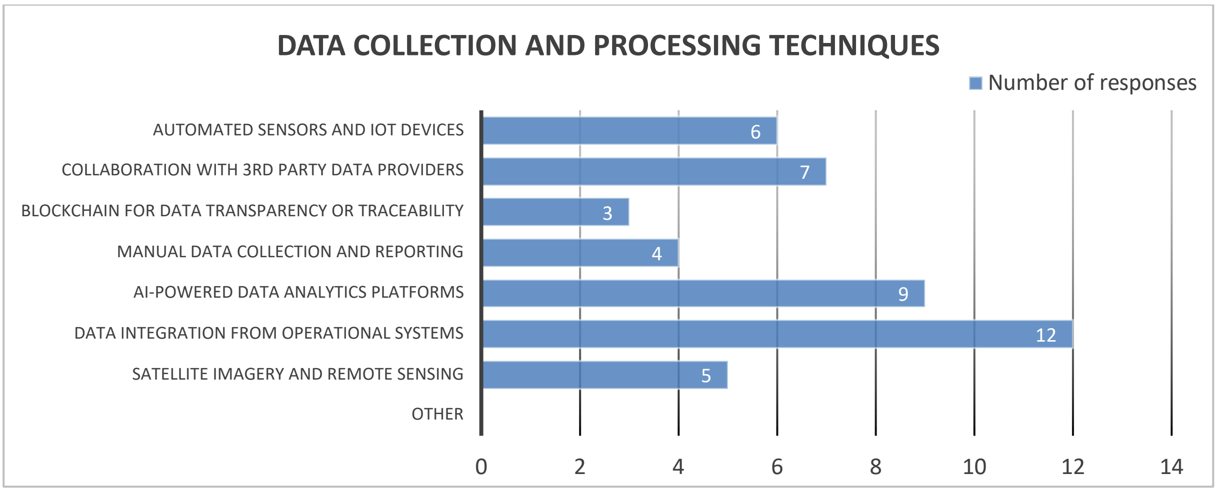

Figure 18 Organization's data collection and processing techniques related to AI applications.

The distribution of data collection and processing techniques obtained is as follows:

1. Data integration from operational systems (52%, 12 respondents);
2. AI-powered data analytics platforms (39%, 9 respondents);
3. Collaboration with 3rd party data providers (30%, 7 respondents);
4. Automated sensors and IoT devices (26%, 6 respondents);
5. Satellite imagery and remote sensing (22%, 5 respondents);
6. Manual data collection and reporting (17%, 4 respondents);
7. Blockchain for data transparency or traceability (13%, 3 respondents).

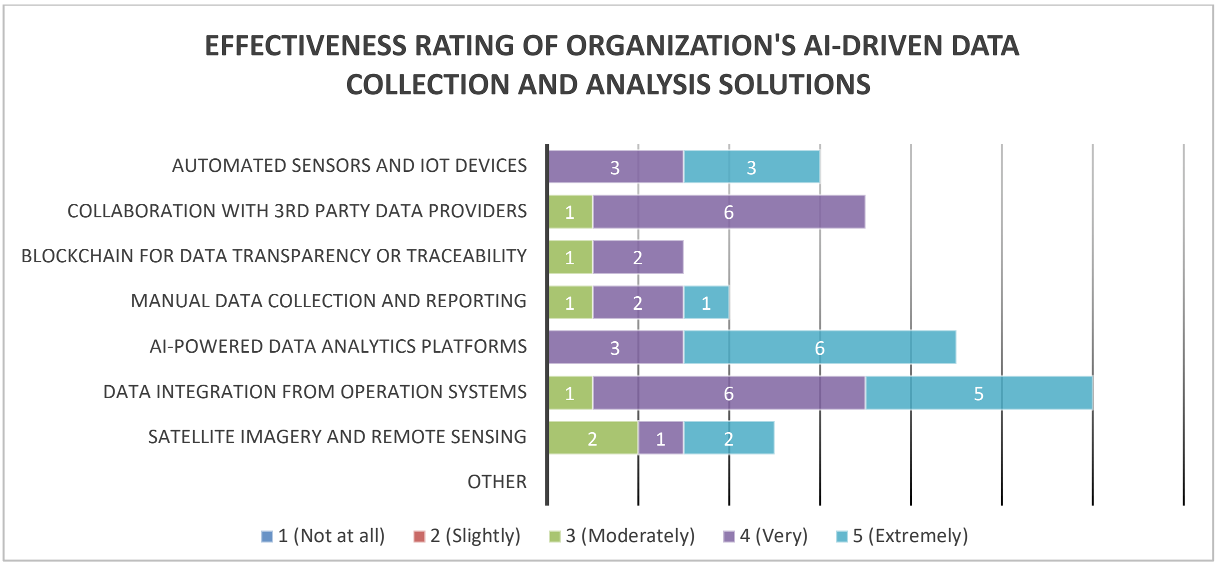

Figure 19 Organization's AI-driven data collection and analysis solutions effectiveness ranking.

Similarly to the previous survey sections, a question was made regarding the perceived effectiveness on the AI-driven data collection and analysis solutions used, as shown in Figure 19 above. When examining both adoption rates and effectiveness ratings, several patterns emerge:

Data integration from operational systems leads in both adoption (52%) and effectiveness (4.2 out of 5.0). This strong correlation between high adoption and high effectiveness suggests that organizations have successfully leveraged their existing infrastructure for environmental data collection, validating this approach as both practical and impactful.

AI-powered data analytics platforms show the 2nd highest adoption rate (39%) with a strong effectiveness rating of 4.0. This alignment between adoption and effectiveness indicates that organizations investing in dedicated AI platforms are seeing substantial returns on their investments.

Collaboration with 3rd party data providers (30% adoption, 3.8 effectiveness) demonstrates that while used by fewer organizations, these partnerships deliver meaningful value. The relatively high effectiveness rating suggests that organizations might benefit from increased collaboration.

Automated sensors and IoT devices (26% adoption, 3.9 effectiveness) and satellite imagery and remote sensing (22% adoption, 3.7 effectiveness) show lower adoption rates but strong effectiveness ratings. This pattern suggests these technologies, while potentially requiring more significant investment or technical expertise, provide substantial value when implemented.

Manual data collection and reporting despite its lower adoption rate (17%), maintains a respectable effectiveness rating (3.5). This indicates that while not being the most advanced approach, traditional data collection methods still play an important role, or when no other options are available.

Blockchain for data transparency or traceability shows the lowest adoption rate (13%) but achieves a solid effectiveness rating (3.6), suggesting that while still emerging, this technology offers promising results for organizations that have implemented it.

The data illustrates several key trends:

→ All techniques maintain effectiveness ratings above 3.5, indicating that organizations are generally successful with their chosen approaches, regardless of the specific method used.

→ More traditional and established techniques (e.g. data integration and analytics platforms) show higher adoption rates and very strong effectiveness ratings, suggesting these should be priority considerations for organizations beginning their AI sustainability initiatives.

→ Newer technologies (e.g. IoT devices or blockchain) demonstrate strong effectiveness despite lower adoption, indicating potential growth areas as these technologies mature and become more accessible.

→ The combination of adoption and effectiveness ratings suggest a maturing field where organizations have identified reliable methods and continue to explore new approaches.

The survey findings regarding data collection and processing techniques demonstrate strong alignment with the fundamental AI requirements outlined in section 2.1.1, particularly concerning knowledge representation and data management as presented by Russell & Norvig (2022). The predominance of data integration from operational systems (52%) and AI-powered analytics platforms (39%) reflects the practical implementation of the theoretical frameworks discussed by Lecun et al. (2015) regarding the importance of integrated data systems for effective AI deployment. Moreover, the adoption of automated sensors and IoT devices (26%) aligns with the technological progression described by Huang et al. (2021) in section 2.3.2, where such technologies were identified as crucial for real-time environmental monitoring and data collection in manufacturing contexts.

The relatively low adoption of blockchain technology (13%), despite its solid effectiveness rating (3.6), mirrors the emerging nature of this technology as discussed in the European regulatory framework in section 2.2.1, particularly in the context of the EU's approach to data traceability ((European Commission, 2021). The emphasis on data quality and integration methods also reflects the regulatory requirements outlined by Díaz-Rodríguez et al. (2023) in section 2.2.1, particularly regarding data transparency and traceability in environmental monitoring systems. This correlation between survey findings and regulatory frameworks suggests that organizations are actively aligning their data collection practices with both technological capabilities and compliance requirements as recommended in the AI Act's risk-based approach discussed in section 2.2.1.

4.1.5. Client Support and Outcomes

The survey also investigated how organizations leverage AI-based solutions to assist their clients in improving environmental sustainability outcomes, thus being a more consultant company type focused question. Figure 20 illustrates the most common support services offered.

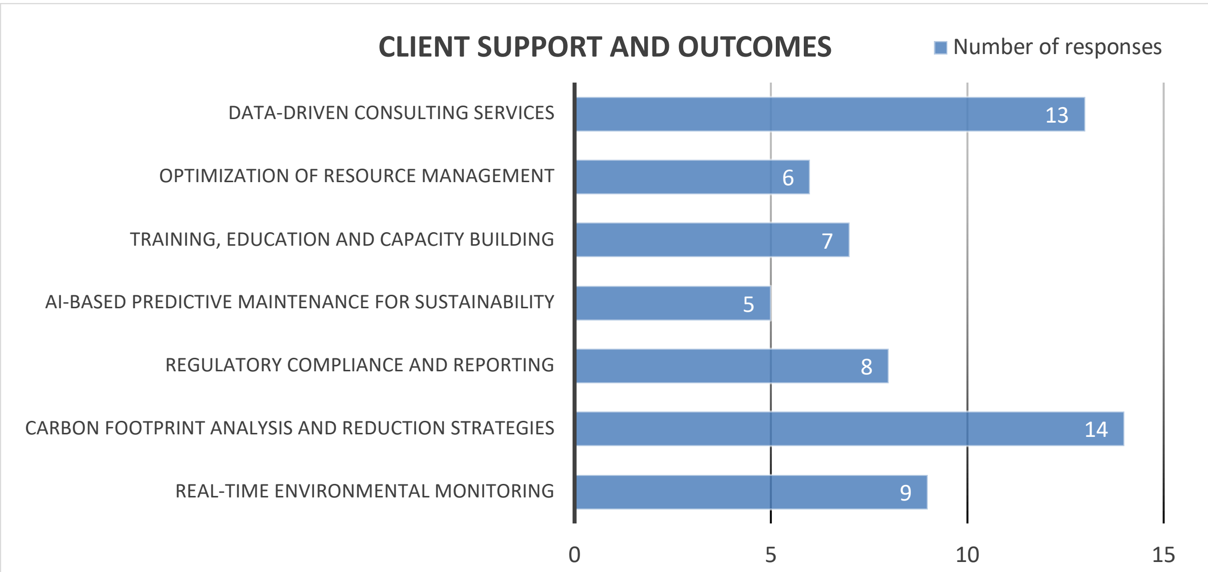

Figure 20 Client support and outcomes in AI-based environmental sustainability services.

Based on the 23 total respondents, the distribution of support services provided is as follows:

1. Carbon footprint analysis and reduction strategies (61%, 14 respondents);
2. Data-driven consulting services (57%, 13 respondents);
3. Real-time environmental monitoring (39%, 9 respondents);
4. Regulatory compliance and reporting (35%, 8 respondents);
5. Training, education and capacity building (30%, 7 respondents);
6. Optimization of resource management (26%, 6 respondents);
7. AI-based predictive maintenance for sustainability (22%, 5 respondents).

Adding to Figure 21, which presents the effectiveness rating perceived by the respondents on client support while using AI-based solutions or services, on a scale from 1 to 5.

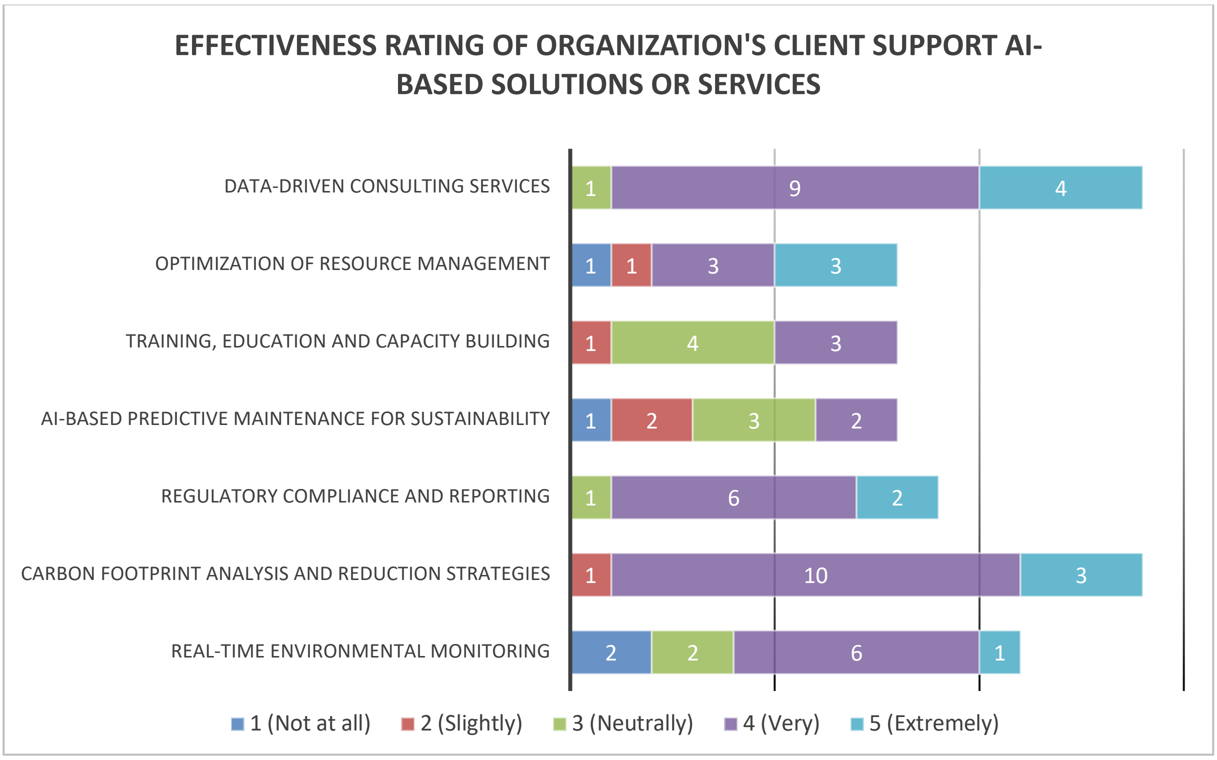

Figure 21 Effectiveness rating of organization's client support AI-based solutions or services.

The data reveals a diverse range of AI-powered services which are offered to clients for environmental sustainability actions, with some trends which can be correlated from both Figures 20 and 21 above.

Carbon footprint analysis and reduction strategies emerged as the most prevalent service, offered by 61% of respondents, with a strong effectiveness rating of 4.2 out of 5. This high adoption rate coupled with superior effectiveness suggests that AI solutions are particularly well-suited for carbon-related analyses and interventions. The strong performance in this category aligns with growing corporate priorities around greenhouse gas emissions reduction and climate change mitigation.

Data-driven consulting services ranked second in adoption (57%) and achieved an effectiveness rating of 3.9. This robust effectiveness score validates the value of AI-enhanced analytical approaches in sustainability consulting, indicating that organizations can effectively translate AI-derived insights into actionable recommendations for clients.

Real-time environmental monitoring services, implemented by 39% of respondents, received an effectiveness rating of 3.8. This relatively high effectiveness score, despite moderate adoption, suggests that organizations successfully deploying these solutions achieve meaningful results in continuous environmental impact assessment and management.

Regulatory compliance and reporting services (35% adoption) obtained an effectiveness rating of 3.7. While the adoption rate is moderate, the solid effectiveness score indicates that AI solutions are proving valuable in helping organizations navigate complex environmental regulatory requirements.

Training, education and capacity building initiatives (30% adoption) achieved an effectiveness rating of 3.6. This score suggests that AI-enhanced educational approaches are delivering positive results in building organizational capabilities around environmental sustainability.

Optimization of resource management services, offered by 26% of respondents, received one of the highest effectiveness ratings at 4.1. This notable discrepancy between adoption rate and effectiveness score suggests an underutilized opportunity, potentially due to implementation complexity or resource constraints rather than service effectiveness.

AI-based predictive maintenance for sustainability, while showing the lowest adoption rate (22%), achieved a respectable effectiveness rating of 3.5. This indicates that while implementation may be challenging, organizations that successfully deploy these solutions realize meaningful benefits.

The effectiveness ratings demonstrate consistently positive outcomes across all service categories, with scores ranging from 3.5 to 4.2. This narrow band of high effectiveness ratings suggests that organizations have generally succeeded in developing and implementing valuable AI-based sustainability services, regardless of the specific focus area.

The combination of adoption rates and effectiveness scores reveals several strategic insights:

→ Services with high adoption rates consistently demonstrate strong effectiveness, validating organizational investment decisions in these areas;

→ Several services with lower adoption rates but high effectiveness scores (particularly resource management optimization) may represent growth opportunities;

→ The general achievement of effectiveness ratings above 3.5 indicates a mature service landscape where organizations have developed expertise in applying AI-based solutions to environmental sustainability challenges.

The survey results regarding client support and outcomes demonstrate a significant correlation with the AI-based environmental sustainability solutions discussed in section 2.3.3. of the literature review. The high prevalence of carbon footprint analysis and reduction strategies (61%) among service offerings directly aligns with the practical applications detailed by Rolnick et al. (2019), particularly regarding climate change mitigation efforts. The strong focus on data-driven consulting services (57%) reflects the industry trends identified by Wang et al. (2018) in section 2.3.2, where AI-enhanced analytics are increasingly central to business decision-making processes.

Moving to Figure 22 below, gathers an average percentage of success by organizations in the implementation of AI solutions in different measures of environmental sustainability. It shows the number of responses, as well as the perceived average percentage of success rates for each specified measure, presenting also minimum (Min) and maximum (Max) values obtained from the survey.

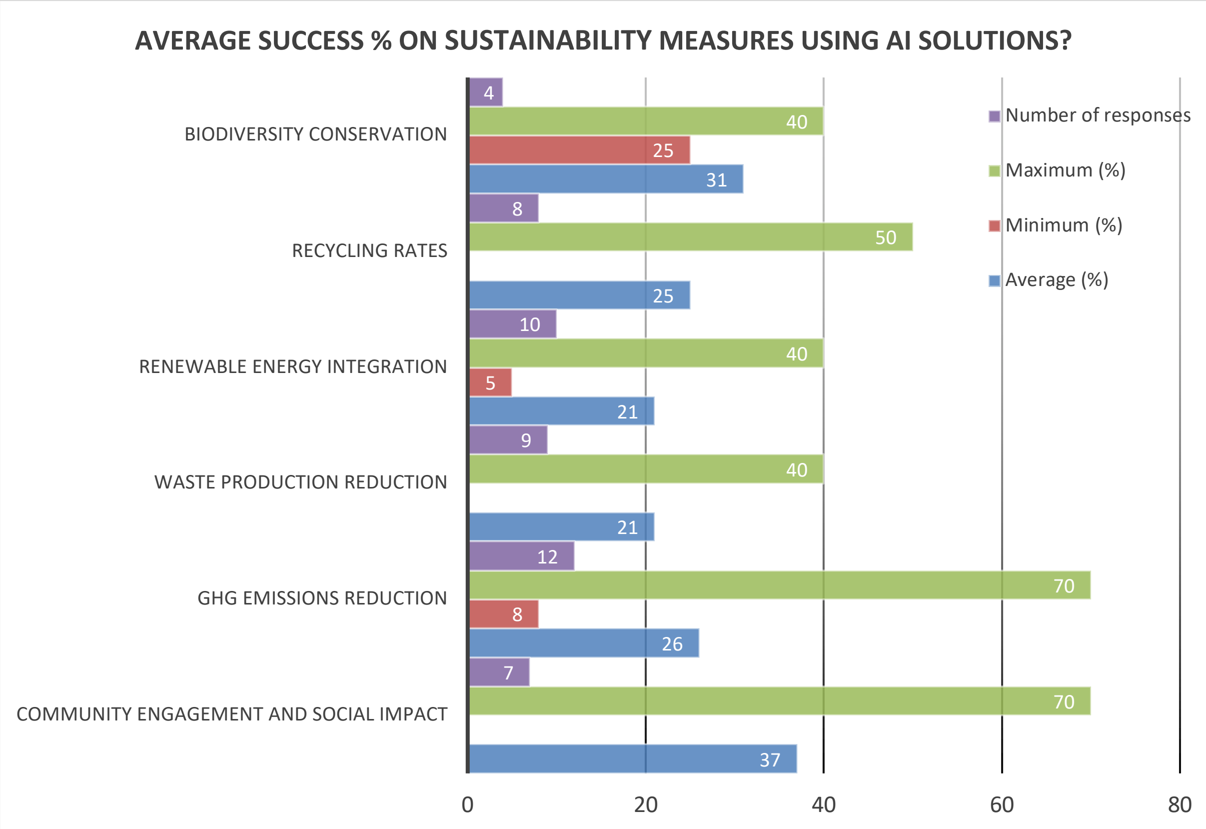

Figure 22 Average percentage of success on sustainability measures using AI solutions.

The results are as follows, by order of number of responses obtained:

1. GHG emissions reduction (12 responses): Max: 70%, Min: 8%, Average: 26%;
2. Renewable energy integration (10 responses): Max: 40%, Min: 5%, Average: 21%;
3. Waste production reduction (9 responses): Max: 40%, Min: 0%, Average: 21%;
4. Recycling rates (8 responses): Max: 50%, Min: N/A, Average: 25%;
5. Community engagement and social impact (7 responses): Max: 70%, Min: 0%, Average: 37%;
6. Biodiversity conservation (4 responses): Max: 40%, Min: 25%, Average: 31%.

Some insights can be concluded from this data, existing a significant variability between min/max success rates across all categories, indicating that effectiveness of AI solutions can vary greatly depending on context. The highest success rates of 70% for both Community engagement and GHG emissions reduction suggest that AI solutions can have a substantial impact in these areas. Community engagement and social impact shows the highest average success rate (37%), indicating that AI solutions are particularly effective in this area, possibly due to improved communication strategies.

While GHG emissions reduction has a high Max (70%), its average (26%) is lower, suggesting that while AI can be very effective in this area, results are not consistent. Waste production reduction and renewable energy integration show lower average success rates (21% each), indicating these may be more challenging areas for AI implementation or that the technology is still evolving in this domain. Despite having fewest responses, Biodiversity conservation shows a relatively high average success rate (31.25%), suggesting positive results in this area although seldomly applied. The lack of a minimum value for Recycling rates suggests incomplete data or that some respondents didn't provide data, which could affect the interpretation of results.

The reported success rates in various sustainability measures provide empirical validation for the potential impacts discussed by Peter Clutton-Brock et al. (2021) in section 2.3.3. The notable variations in GHG emissions reduction (from 8% to 70%) correspond with the case studies presented in Table 6, particularly the examples of *Climate TRACE* and *Arup Neuron* system implementations.

The community engagement success rates (average 37%) align with the findings of Palomares et al. (2021) in section 2.1.3 of the literature review regarding AI's role in achieving social aspects of sustainable development goals. These findings again support Vinuesa et al. (2020) assertion that while AI can significantly impact environmental sustainability, outcomes can vary considerably based on context and approach.

Thus, Figure 22 demonstrates that AI solutions are having an impact perceived as positive by the respondents, across various sustainability measures. The ranges between Min/Max values highlight the importance of proper implementation and possibly indicate that the field is still maturing, with some companies achieving better results than others. The data also suggests that while AI is proving to be effective in areas such as community engagement and GHG emissions reduction, there's still room for improvement in waste reduction or renewable energy integration. This could indicate areas where further AI-related R&D could yield benefits for environmental sustainability efforts.

4.1.6. AI Implementation Challenges

Despite the promising results, organizations still face several challenges in implementing AI-based solutions for environmental sustainability. Figure 23 below outlines the primary challenges reported by the survey respondents.

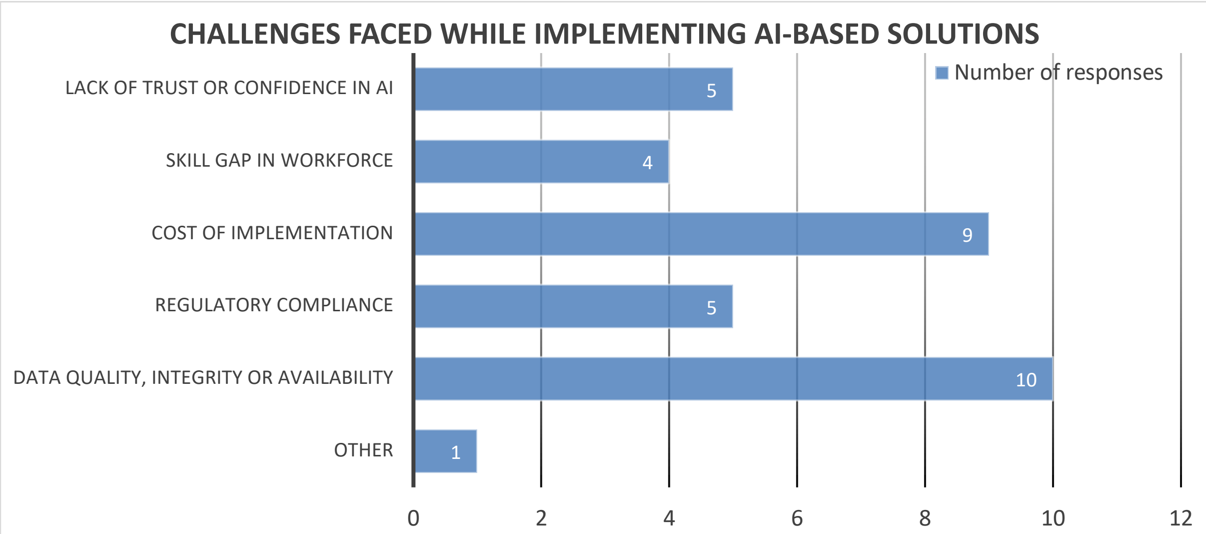

Figure 23 Challenges faced by organizations while implementing AI-based solutions for environmental sustainability.

Based on the survey responses, the challenges are ranked as follows, from major to minor:

1. Data quality, integrity or availability (43%, 10 responses)
2. Cost of implementation (39%, 9 responses)
3. Regulatory compliance (22%, 5 responses)
4. Lack of trust or confidence in ai (22%, 5 responses)
5. Skill gap in workforce (17%, 4 responses)
6. Other (4%, 1 response)

As shown, the most frequently cited challenge is data quality, integrity or availability. This aligns with the critical role of data in AI systems and suggests that organizations are struggling with obtaining, maintaining, and ensuring the reliability of the data needed for effective AI implementation.

A high number of responses for cost of implementation indicates that financial considerations are a significant barrier for AI adoption in environmental sustainability efforts. This reflects potential high upfront costs of AI systems or uncertainty on investment returns. Both regulatory compliance and lack of trust or confidence in AI received an equal number of responses, highlighting the challenges of navigating complex regulatory frameworks and overcoming skepticism about AI technologies.

The skill gap in workforce, while not the top challenge, it's still significant. This indicates that organizations are facing difficulties in finding or developing talent with the necessary expertise to implement and manage AI systems. The "other" category, albeit with only one response, suggests that there may be unique or emerging challenges not captured by the main categories. The information given by one respondent was "consistency and explainability" showing the difficulty in maintaining a consistent source of data and a correct manner of presenting the same data.

The implementation challenges identified in the survey closely mirror the barriers discussed in section 2.1.1 on the examination of AI fundamentals. The predominance of data quality and integrity concerns (43%) as the primary challenge aligns with Floridi et al. (2018) emphasis on data governance and quality as critical ethical principles for AI implementation. This finding also provides empirical validation for the theoretical framework of AI requirements outlined by Díaz-Rodríguez et al. (2023) in Figure 3, particularly regarding the technical robustness and safety pillars of trustworthy AI.

The significant concern regarding implementation costs (39%) and regulatory compliance (22%) reflects the practical challenges discussed in section 2.2 analysis of regulatory frameworks, regarding the complexities introduced by the AI Act and its risk-based approach detailed in Figure 7. The relatively lower concern about workforce skill gaps (17%) contrasts with the challenges identified by AMA in Portugal's AI readiness assessment in Figure 6, however aligning with the growing maturity of AI technologies discussed by Bellini et al. (2022) in section 2.1.2 which presented a brief history of AI. This suggests that organizations have made progress in addressing the technical expertise challenges, though data quality and cost concerns remain significant barriers to implementation.

Overall, this chart demonstrates that while AI holds significant promise for environmental sustainability applications, its implementation still has some obstacles along the way. The predominance of data-related challenges underscores the fundamental importance of high-quality, reliable data in AI systems.

The significant concerns about cost and regulatory compliance suggest that there may be a role for policy interventions or industry collaborations to reduce these barriers. The trust and skill gap issues evidence the need for better communication about AI, as well as increased investment in training and education, as addressing these challenges will be crucial for a broader adoption and more effective implementation of AI in environmental sustainability fields.

4.1.7. Future Outlook on AI

Looking to the future, respondents envisioned several roles for AI in the health and tech industry.

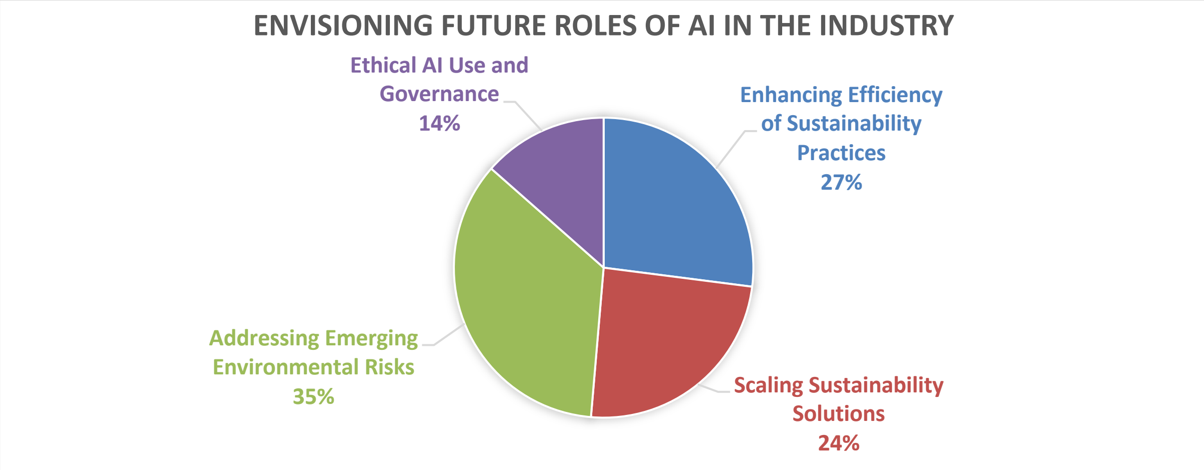

Figure 24 Future roles of AI applied to environmental sustainability in the health and technology industry.

The responses are categorized into four main areas in Figure 24, by order of importance:

1. Addressing emerging environmental risks (35%, 13 responses)
2. Enhancing efficiency of sustainability practices (27%, 10 responses)
3. Scaling sustainability solutions (24%, 9 responses)
4. Ethical AI use and governance (14%, 5 responses)

It can be established, that the largest share (35%) is allocated to addressing emerging environmental risks. This suggests that professionals see AI playing a crucial role in identifying, predicting, and mitigating new environmental challenges. It reflects a proactive approach to environmental management and the recognition of AI's enormous potential in complex risk assessment. A significant portion (27%) also envisions AI enhancing the efficiency of existing sustainability practices. This indicates an expectation that AI will optimize current processes, potentially leading to more effective resource use, reduced waste and improved environmental outcomes.

Nearly a quarter (24%) of respondents see AI as key to scaling sustainability solutions, suggesting a recognition of AI's potential to make sustainable practices more widespread and impactful, possibly by making them more accessible, cost-effective or adaptable. While it has the smallest share, 14% of responses focus on ethical AI use and governance, exposes the awareness of responsible AI deployment in environmental contexts, considering fairness, transparency and accountability concepts.

The relatively even distribution across the first three categories (35%, 27%, and 24%) suggests a balanced view of AI's future roles, recognizing its potential contributions in multiple areas of environmental sustainability. The distribution of future roles, particularly the focus on emerging risks and efficiency enhancement, also reflects the opportunities identified in Hassan et al. (2023) and Rolnick et al. (2019) regarding AI's potential in environmental monitoring and optimization. This alignment between industry expectations and academic literature suggests that organizations are well-positioned to implement the types of solutions documented in section 2.3.3 on AI-based environmental solutions.

Comprehensively, the pie chart in Figure 24 demonstrates that industry professionals have high expectations for AI's future role in achieving environmental sustainability. The emphasis on addressing emerging risks suggests a forward-looking perspective, recognizing AI's potential to help navigate an increasingly complex environmental landscape. The inclusion of ethical considerations, while smaller in proportion, is significant. It suggests an awareness of the potential pitfalls of AI and the need for responsible development and deployment of these technologies in environmental contexts, not forgetting the importance of developing robust ethical frameworks and governance structures to ensure that AI is deployed responsibly in pursuit of environmental sustainability goals.

The focus on efficiency and scaling indicates an expectation that AI will not only improve existing practices but also make sustainable solutions more widely applicable and impactful worldwide. This could become crucial for addressing global environmental challenges at scale, providing for ultimate solution on the upbringing of a sustainable balance between human-made industries and nature conservation and preservation.

Coming finally to the last research survey Figure 25 below, it aims to illustrate the opinions of professionals regarding the timeframe in which AI is expected to significantly impact sustainability practices in the industry.

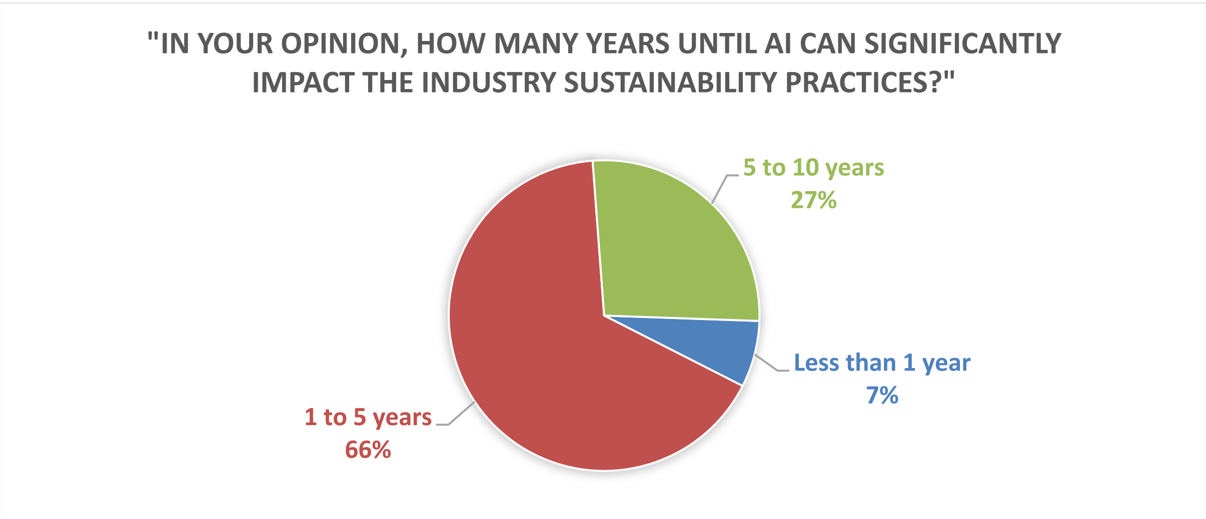

Figure 25 Expected timeline for AI's significant impact on industry sustainability practices, according to survey respondents.

The responses are categorized into four different time ranges, by order of number of selections:

1. 1 to 5 years (66%)
2. 5 to 10 years (27%)
3. Less than 1 year (7%)
4. More than 20 years (0% responses)

Most respondents (66%) believe that AI will significantly impact industry sustainability practices within the next 1 to 5 years. This indicates a high level of confidence in the relatively rapid development and integration of AI technologies in sustainability efforts. A significant minority (27%) anticipate that it will take 5 to 10 years for AI to have a substantial impact. This group may be considering factors such as the time needed for widespread adoption, regulatory adjustments or the development of more advanced, budget friendly AI. A small portion (7%) believe that AI will significantly impact sustainability practices in less than a year. This suggests that some professionals see AI as already poised to transform the industry in the very near term. Notably, no respondents selected the more than 20 years" option. The lack of long-term projections strongly indicates that industry professionals do not foresee major delays or obstacles in the integration of AI into sustainability practices. Cumulatively, 100% of respondents expect significant AI impact within the next decade, with the majority anticipating this impact to happen in the next 5 years. This reflects a unanimous confidence in AI's potential to transform sustainability practices in the relatively near future.

Overall, this chart demonstrates a high level of optimism regarding the timeline for AI's impact on industry sustainability practices. The strong consensus around a 1-to-5-year timeframe, coupled with the complete absence of long-term projections, suggests that professionals working in the AI industry strongly believe that the necessary technologies and implementation strategies are not only well underway, but are also expected to yield significant results in the upcoming years. However, this data presents both opportunities and challenges for the industry. It suggests a need for immediate and proactive planning and investment in AI tech for sustainability, underlining the importance of managing these highly optimistic expectations and preparing for the practical challenges of implementing these technologies in real-world contexts within a relatively short timeframe.

4.1.8. Additional Insights

To gather further perspectives on the use of AI in environmental sustainability efforts, respondents were asked the following open-ended question, in a concluding manner to the survey: "*Is there any additional information or insights you would like to share regarding your organization's approach to using AI for environmental sustainability*?"

This question aimed to capture any approaches, challenges or observations that might not have been covered in the structured parts of the research survey. Out of all survey participants, only one respondent provided additional information. This response offers a valuable glimpse into the practical application of AI in environmental sustainability efforts, particularly for large companies: "*Large companies have a very semantically heterogenous inventory of physical flows and activities. Computing their footprint cannot be achieved at scale without a first pass with AI. AI is also used to assess potential issues with the matching process and help human experts quickly identify where further manual validation is required."* This single observation indicates the respondent highlights the challenge of "*semantically heterogeneous*" inventories in large companies, emphasizing the complexity of data involved in sustainability efforts for major corporations, noting that footprint computation at scale is not feasible without AI and indicating that AI is not just beneficial but essential for comprehensive sustainability assessments in large organizations.

It can also be inferred that AI's role in identifying potential issues in the data matching process suggests its application in ensuring data quality and accuracy, describing a hybrid approach where AI assists human experts by directing their attention to areas requiring manual validation, optimizing the use of human expertise, also known as Human-in-the-Loop (HITL). The mention of a "*first pass with AI*" implies an iterative approach to footprint assessment, where AI provides an initial iterative analysis followed by targeted HITL intervention. This individual insight, while limited to a single response, provides a concrete example of how AI is being integrated into environmental sustainability practices. It highlights AI's crucial role in handling the volume and complexity of data generated by large companies, while also emphasizing the continued importance of human expertise in the process.

The low response rate to this open-ended question (only 1 out of all 23 participants) could suggest that most respondents felt they had adequately expressed their views through the structured parts of the survey or that some organizations may be hesitant to share detailed information about their AI approaches, possibly due to competitive concerns, proprietary or patent-related information or the nascent state of their AI technologies.

While we are not able to draw definitive and broad proven conclusions from a single response or from the small number of respondents of the survey, this insight offers a valuable perspective on the practical challenges and solutions in implementing AI for environmental sustainability in large corporate settings. It brings out the potential of AI to enable more comprehensive and efficient sustainability practices, particularly in complex organizational environments and denoting AI's role not only as a data processing tool, but also as a crucial component in a sophisticated system that combines machine efficiency with human expertise. This approach seems to address the challenges of scale, complexity and accuracy in environmental footprint assessments, potentially enabling more comprehensive and reliable sustainability practices for medium-sized or large corporations.

CHAPTER 5

Conclusions, Limitations and Opportunities

Chapter 5 synthesizes the key findings from both the literature review and empirical research to address the study's core research questions regarding AI's role in environmental sustainability within the health and technology industries. Building on the theoretical frameworks examined in Chapter 2 and the survey results analyzed in Chapter 4, this chapter presents major conclusions about the current state of AI implementation, its effectiveness in driving environmental sustainability, as well as future opportunities. This concluding chapter firstly presents major conclusions drawn from the research, then acknowledges limitations of the study before exploring the existing opportunities for future development and closing with final reflections on AI's transformative potential in environmental sustainability.

5.1. Major Conclusions

This research has yielded several significant conclusions regarding the role of AI in achieving environmental sustainability in the health and technological industries. Through comprehensive analysis of regulatory frameworks and primary data collection source via an online questionnaire survey, this study has addressed its three core research questions, revealing both the current state and future potential of AI in environmental sustainability efforts.

In addressing the first research question regarding AI's definition and efficient use, the investigation revealed several significant findings. AI encompasses a wide range of technologies, with ML emerging as the dominant capability, employed by 57% of surveyed organizations. The research demonstrated that safe and efficient AI implementation requires robust data management practices, as evidenced by the majority of organizations prioritizing data integration from operational systems (52%).

Data quality and integrity emerged as the fundamental requirement for efficient and safe AI use, though paradoxically (maybe due to its abundant use), it also represents the primary challenge, cited by 43% of respondents. The findings indicated that successful AI implementation requires a balanced approach combining technical expertise with human judgment, particularly in environmental applications, though only 14% of respondents specifically emphasized ethical AI governance.

Regarding the second research question concerning global AI regulatory frameworks, the analysis revealed a complex and rapidly evolving landscape across national, regional and international levels. Organizations are actively working to align with these frameworks, with regulatory compliance cited as a key focus area by 35% of survey respondents. The EU's AI Act emerged as a significant development, representing the first comprehensive attempt to regulate AI systems based on their potential risk level. The research revealed that organizations are preparing for increased regulatory oversight, with 35% already providing regulatory compliance support services to their clients.

The third and last research question, examining the current state of AI implementation in medical and technological companies, yielded comprehensive insights into capabilities, applications and methodologies. Organizations demonstrated strong environmental applications focus, with 70% utilizing AI for data collection and analysis and 52% employing it for environmental impact assessment. The emphasis on emission reduction strategies (43%) and environmental predictive modeling (39%) indicates AI's central role in environmental sustainability efforts. The research uncovered sophisticated approaches to data handling, with organizations employing multiple methodologies beyond the predominant use of operational system integration. The implementation of automated sensors and IoT devices (26%) suggests a growing trend toward real-time environmental monitoring capabilities.

The study revealed comprehensive service offerings, with carbon footprint analysis leading at 61% of respondents, followed by data-driven consulting services at 57%. Implementation challenges identified include data quality concerns, implementation costs, regulatory compliance complexity, and trust issues in AI systems. Despite these challenges, the findings revealed strong industry confidence, with 66% of respondents expecting AI to substantially influence sustainability practices within the next 1-to-5 years. Future development areas focus on addressing emerging environmental risks (35%), enhancing sustainability practice efficiency (27%), and scaling solutions (24%).

This investigation ultimately concludes that successful AI implementation for environmental sustainability depends on the careful orchestration of robust data management practices, clear regulatory compliance frameworks, adequate technical infrastructure and specific environmental metrics, all while maintaining a thoughtful balance between automation and human oversight. These findings provide a foundation for organizations seeking to implement AI for environmental sustainability, while highlighting areas requiring further R&D. The demonstrated potential of AI in advancing environmental sustainability practices, coupled with the identified challenges and future perspectives detailed ahead, suggests a transformative period ahead for both the health and technology sectors in their pursuit of environmental sustainability goals.

5.2. Limitations to the Research

Despite the valuable insights gained, this study encountered several significant limitations, primarily centered around the research survey and data collection process:

1. Low response rate: The most notable limitation was the low number of responses to the research survey. This small sample size (23 responses) significantly impacts the statistical validity and generalizability of the survey results.
2. Limited representativeness: Due to the low response rate, the survey data may not be fully representative of the broader industry perspectives on AI and environmental sustainability.
3. Potential response bias: Those who did respond to the survey might represent a specific subset of professionals more knowledgeable in certain topics, potentially skewing the results.
4. Depth of insights: The limited number of responses restricted the depth of analysis that could be done from the survey data, particularly regarding nuanced or sector-specific applications.
5. Difficulty in data collection: The challenges faced in obtaining survey responses highlight the difficulty of collecting primary data in this field, possibly due to factors such as time constraints of professionals, confidentiality concerns or lack of engagement with academic research.
6. Geographical and sectoral representation: The low response rate may have resulted in uneven representation across different geographical areas and subsectors.
7. Temporal limitations: The survey provides only a snapshot of current practices and perspectives, which may be rapidly evolving in the fast-paced fields of AI and sustainability.

These limitations, primarily stemming from the difficulties encountered with the research survey, underline the need for caution in interpreting the results. They also highlight the challenges of conducting research in this field and suggest areas where future studies might focus on developing more effective strategies for data collection and industry engagement.

5.3. Opportunities for AI and Sustainability

Despite the limitations encountered in this research, the study has unveiled several promising avenues for future development and research in the intersection of AI and environmental sustainability within the health and tech industries. Future research could focus on developing more sophisticated AI-driven systems for environmental data collection and analysis, enabling more accurate monitoring of sustainability efforts and impacts. As corroborated by Vinuesa et al. (2020) and many other authors, AI has significant potential to support all 17 SDGs through improved monitoring and data analysis.

The research findings, combining literature review and survey results, reveal several promising avenues for future development in AI-based environmental sustainability within the health and technological sectors, which can be identified in the summarized in several points. In risk management, opportunities focus on developing enhanced predictive modeling capabilities, real-time monitoring systems, and advanced tools for assessing climate-related challenges. Efficiency enhancement presents opportunities through improved AI algorithms for resource optimization, better integration with IoT devices for environmental monitoring, and development of more energy-efficient AI systems.

Scaling solutions represents another crucial area, emphasizing the need for more accessible and cost-effective AI implementations, standardization of solutions for wider market adoption and creation of sector-specific frameworks. The timeline for implementation suggests opportunities in developing rapid-deployment solutions, creating streamlined implementation frameworks and investing in short-term sustainability projects. Data quality and integration remain critical, with opportunities surging in improving collection methodologies, standardizing environmental metrics formats and enhancing validation systems.

In the regulatory space, opportunities arise in developing AI systems that automatically adapt to changing regulations, creating predictive compliance tools and integrating harmonized requirements into AI design processes. Technical innovation opportunities can encompass developing energy-efficient algorithms, integrating emerging technologies such as blockchain and creating sophisticated environmental modeling systems. Finally, practical implementation opportunities focus on developing cost-effective solutions for smaller organizations, creating frameworks that address adoption barriers and designing scalable solutions that can grow according to the right organizational needs.

These opportunities are particularly pertinent given the pressing nature of environmental challenges and the demonstrated potential of AI to contribute to their resolution. The combination of high industry confidence and clearly identified challenges provides a structured framework for future development, emphasizing the need for practical, scalable and efficient solutions that can be implemented within a relatively short timeframe, while addressing current limitations in data quality, cost, legislation and expertise.

Future research should focus on developing these opportunities while maintaining awareness of ethical considerations and ensuring that developments align with broader and internationally aligned sustainability goals. This balanced approach will be crucial in realizing the full potential of AI in advancing environmental sustainability within the health and technological sectors, which surely will also trigger growth and advancements in various sectors besides health and tech.

5.4. Closing Remarks

All these findings, either through the peer-reviewed literature or research survey results, emphasize the near-term or long-term opportunities and the importance of the ongoing potential for AI to drive significant advancements in environmental sustainability methodologies and processes within and beyond the health and technological industries. Pursuing these avenues could lead to more effective, efficient and comprehensive approaches to addressing global environmental challenges, as fast as possible for their implementation, in a supported and scaled manner.

This dynamic and ever-expanding nature of AI calls out for an open-ended dialogue, as well as adaptive global governance approaches to harness its benefits while mitigating potential risks, challenges and, most importantly, human-caused global warming consequences which are already felt across the globe. Following the good examples and proven results obtained from international organizations, industries are able to share knowledge and concrete-proof data on successfully implemented applications and procedures, in order to spread the word on best practices across multiple fields of work that are responsible for environmental damage, while fighting to preserve and protect all fauna and flora.

The future of AI will depend not only on technological and scientific R&D advancements but also on our modern societies ability to navigate the complex and multilayered ethical, social, cultural, religious and philosophical settings that arise in the 21st century, as Artificial Intelligence becomes an increasingly integral part of our world, having to grow alongside it and in harmony with it. And, as much as possible, to use it for our best advantage in ethical, balanced, efficient, sustainable and justified ways, as well as providing the care, protection and well-being for all sentient or non-sentient living creatures, that we share this beautiful, rare and unique planet Earth with.

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Annexes

Annex A – Examples of AI Systems and respective Articles of the Universal Declaration of Human Rights which are impacted by them. Source: AMA, 2021

ARTIFICIAL INTELLIGENCE SYSTEMS	*HUMAN RIGHTS ARTICLES*
Data collection and analysis using AI systems	*2, 7, 12, 18, 19*
Prediction of sexual conduct by ML and facial recognition	*1, 2, 3, 7, 11, 12, 16, 18, 23*
Predictive ML models based on location data - estimating age, gender, occupation, marital status and mobility	*12, 13, 18, 19, 20, 27, 30*
Dissemination of culture (music, cinema, art) by AI systems	*1, 2, 19, 23, 27*
ML models for identifying pornographic, violent or politically sensitive content	*10, 12, 18, 19, 20, 23, 30*
Content indexing algorithms in search engines	*18, 19, 21, 26, 27, 30*
Algorithms that determine the content of a user's news feed and with whom the content is shared	*18, 19, 21, 26, 27*
Online content moderation - compliance with standards	*2, 3, 12, 18, 19, 21, 23, 27, 30*
Writing assistance SW for dissemination info - preparation of new stories or other content	*18, 19, 23, 30*
Content classification systems and creation and reinforcement of filter bubbles	12, 18, 19, 21, 27, 30
Personalized advertisements, based on user behavior	2, 18, 19, 21, 27
Deep fakes	*18, 19, 21, 27, 30*
Influence chatbots	*18, 19, 20, 21*
Social communication platforms with algorithms that estimate viewpoints/ opinions that will receive greater visibility	*2, 18, 19, 21, 27*
Government programs for monitoring social media	*2, 3, 7, 11, 12, 18, 19, 20, 21, 27, 30*
AI systems for flagging publications related to terrorist acts, hate speech, fake news	*2, 3, 7, 11, 12, 18, 19, 20, 21, 27, 30*
Group surveillance systems - of great importance in dictatorial regimes	*2, 3, 18, 19, 20, 23*
Surveillance with facial recognition at voting locations	*2, 18, 19, 21, 27, 30*
Surveillance systems with facial recognition at borders - entry control	*12, 13, 18, 19, 20*
Biometrics in refugee registration and decision recommendation	1, 2, 6, 9, 12, 13, 15, 18, 22, 23, 29, 30
Smart roads and public transport systems with biometric marking	*12, 13*
Surveillance with facial recognition - surveillance drones	*12, 13, 14, 27*
Facial recognition systems and location data from mobile phones and satellite images	*13, 14*
Legal judgment decision systems	*1, 2, 3, 7, 9, 10, 11, 12*
Facial recognition - judicial purposes, centralized government systems for threat recognition	*1, 2, 3, 7, 10, 12, 18, 19, 20*
AI models designed to classify and filter, categorizing individuals, for application in criminal justice	*1, 2, 3, 7, 9, 10, 11, 12*
Criminal justice - recidivism risk scoring	*1, 2, 3, 7, 9, 10, 11, 12*
Predictive ML software to identify language or behaviors that show potential for violence	*1, 2, 3, 7, 10*

Automated weapons	*2, 3, 4, 7, 9, 10, 11*
Access to the financial system - credit scoring	*2, 7, 12, 19, 20, 23, 25, 26*
Healthcare - Robots replacing doctors	*1, 2, 3, 12, 23, 25*
General and reproductive health screening	*1, 2, 12, 16, 23*
Genetic tests	*1, 2, 12, 16, 23*
Health insurance allocation	*2, 3, 12, 22, 25*
Prognosis prediction and recommendations in case of illness	*1, 2, 3, 25*
Pandemic control - with health data and digital surveillance	*2, 3, 12, 25*
Admission of applications to schools - prediction of success	*1, 2, 26*
Teaching by robots	*23, 26*
Education - automatic correction of essays	*1, 12, 19, 23, 25, 26*
Human resources - recruitment and hiring	*2, 12, 19, 20, 23*
Automation of functions	*1, 2, 23, 25*
Virtual assistants	*23*
Virtual translators	*23*
Social assistance - e.g., housing assistance for homeless people	*1, 2, 12, 23*

LEGEND (HUMAN RIGHTS ARTICLES):

1. *Equality in dignity and rights;*
2. *Rights and freedoms without discrimination;*
3. *Right to life, liberty and security of person;*
4. *Prohibition of slavery or servitude;*
5. *Freedom from torture or cruel, inhuman or degrading treatment;*
6. *Right to recognition as a person before the law;*
7. *Equality before the law;*
8. *Right to effective remedy by competent national tribunals;*
9. *Freedom from arbitrary arrest, detention or exile;*
10. *Right to a fair and public hearing by an independent and impartial tribunal;*
11. *Right to be presumed innocent until proved guilty;*
12. *Freedom from arbitrary interference with privacy, family, home or correspondence, and from attacks upon honor and reputation;*
13. *Right to freedom of movement and residence within the borders of each state;*
14. *Right to seek asylum from persecution in other countries;*
15. *Right to a nationality and the freedom to change it;*
16. *Right to marry and to found a family;*
17. *Right to own property;*
18. *Freedom of thought, conscience and religion;*
19. *Freedom of opinion, expression and information;*
20. *Freedom of peaceful assembly and association;*
21. *Right to take part in the government of one's country and freedom to vote in public authority;*
22. *Right to social security;*
23. *Right to work in desirable conditions and to found and join trade unions;*
24. *Right to rest and leisure;*
25. *Right to an adequate standard of living;*
26. *Right to education;*
27. *Right to participate in the cultural life of the community;*
28. *Right to a social and international order articulated in this Declaration;*
29. *Community duties essential to the free and full development of United Nations principles;*
30. *No State, group or person may destroy the rights and freedoms set forth.*

Annex B – The 17 Sustainable Development Goals

Source: https://www.bp.com/content/dam/bp/master-site/en/target-neutral/home/images/carbon-offsetting-projects/UN-SDG-17-goals.jpg

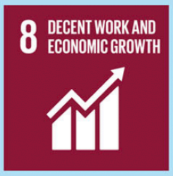
Annex C – Recommendations on using AI in the SDGs dimensions

Source: Palomares et al., 2021

*AI in the SDGs of economic dimension: **Life***

- Identify and predict areas and households under poverty through machine learning algorithms that facilitate decision-making for its prevention or eradication (SDG 1).
- Fight poverty and food shortage through AI and blockchain-driven decision support systems that support fair, transparent and traceable governing processes, enable participatory decisions at large scale –e.g. for resource sharing, assisting vulnerable communities, etc.– and dispel corruption (SDG 1, 2).
- Incentivise *big data* collection, analysis and usage policies, as well as promoting open and unified infrastructures to promote sustainable agriculture, identify and manage health, food and economic sustenance risks and anticipate to them via early warning systems (SDG 1, 2, 3).
- Turn smart cities and territories along with sensor technologies (IoT) into key allies against the spread of epidemic diseases, guaranteeing early warning and action plans for their prevention (SDG 3; *also linked to SDG 11, see Figure 10*).
- Embrace the possibilities of explainable and trustworthy AI systems in healthcare, public health management, prognosis and diagnosis (e.g. using deep learning on medical image data), precision medicine and medication/vaccine development (SDG 3).
- Advance the use of social network, mobile and wearable device data to develop awareness-raising services in social media and personalized AI tools that promote healthy nourishment, exercising and mental health habits, raise sexual health awareness and fight substance abuse across the population among others (SDG 3).

*AI in the SDGs of economic dimension: **Economic and Technological Development***



- Promote strongly scientific and technical (STEM) formative itineraries in higher and postgraduate education to alleviate the so-called technological unemployment (SDG 8; *also linked to SDG 4, see Figure 11*).
- Foster added-value AI initiatives based on innovation in conjunction to (or as replacement to) automation ones to keep a balance between newly created jobs and jobs replaced by the AI (SDG 8, 9).
- Distributed offshoring in manufacturing of replacement pieces, by 3D printing processes and blockchain-based models certification, so that both waste production and pollutant emissions due to transportation of repairing pieces are reduced (SDG 8, 9).
- Catalyse the AI-based digital transformation of the economy, supporting the development of Industry 4.0 concepts specially in SMEs (SDG 9).
- Develop and deploy complex systems that combine IoT, big data, blockchain and predictive AI systems to monitor and certify pollutants, specially in industry and transportation (SDG 9).
- Use smart contracts for reinforcing contaminant reduction commitments of nations, so that penalties can be automatically applied [67] (SDG 9).
- Drive R&D project evaluation processes guided by AI, to detect potential impact of industrial and innovation processes and promote the funding of those with higher environmental, economic or social revenue (SDG 9).

AI in the SDGs of social dimension: ***Social Development***

– Install and support the access by developing countries to adequate infrastructure and resources (e.g. sensor networks) that facilitate massive, effective and efficient data collection in an economically sustainable manner that helps assessing the progress made in SDGs and targets as a whole in an universally consistent way (SDG 17; *also linked to SDG 9, see Figure 9*).
– Explore opportunities and potential of digital twins, augmented reality and virtual reality in urban environment management in order to enhance sustainable cities, their safety, mobility, citizen lives and access to local services (SDG 11).
– Encourage the concept of intelligent city by promoting massive data analysis based on big data and AI models to optimize urban resource management and improve the lives of citizens (SDG 11).
– Leverage advances in robotics, IoT and AI to elaborate action, rescue and risk management plans against incidents and disasters (SDG 11, 16).
– Foster the application of AI and blockchain technologies so that political institutions develop transparent, secure, fair and optimal policies in order to adapt to the changes experienced in society, guided by up-to-date robustness principles and the establishment of liable partnerships between them to advance towards the SDGs (SDG 16, 17).

AI in the SDGs of social dimension: ***Equality***

– Combine augmented reality and virtual reality platforms with AI-guided intelligent tutor systems to develop adaptive learning processes (SDG 4).
– Foster AI guided online learning in technological skills, focused on girls, women and disadvantaged groups, to promote their empowerment and access to the Internet (SDG 4, 5, 10).
– Develop non-biased AI systems focused on data collection and annotation processes, to avoid inequalities in recommendations and decisions (SDG 5, 10).
– Develop AI-driven Natural Language Processing models to detect and warn about malicious and offensive content in social media and the Internet, preventing behaviours and speech motivated by hate (SDG 5, 10).
– Combine AI and blockchain to make participatory governance and political processes more accessible, and to prioritize the visibility, participation and representation of women and disadvantaged groups (SDG 5, 10).

AI in the SDGs of environmental dimension: ***Resources***

- Construct simulation models implemented as digital twins to help in management of water and energy resources, preventing and fighting their contamination, and detecting failures in infrastructures via machine learning (SDG 6, 7).
- Drive edge computing architectures to avoid data storage explosion in data centers, thereby decreasing energy consumption (SDG 7).
- Develop high fidelity predictive models based on deep learning for a better exploitation of renewable energy sources (SDG 7).
- Enhance the management, transparency and security in smart grids through the application of blockchain (SDG 7).
- Apply AI-driven decision support systems involving multiple stakeholders participation to define and develop models for sustainable production and consumption (SDG 12).
- Intensify the joint use of IoT and big data to improve production processes, distribution networks and their resulting contamination effects through sensorization, and obtain deeper insight on consumption habits, patterns and fluctuations (SDG 12; *also linked to SDG 11, see Figure 10*).

AI in the SDGs of environmental dimension: ***Natural Environment***

- Joint use of AI models and IoT devices to predict natural disasters and anticipate human action against their effects (SDG 13).
- Use AI models to predict energy resource needs, optimize the exploitation of green & renewable energy, and improve traffic in cities, to reduce the causes behind climate change (SDG 13).
- Endow least developed countries with ocean monitoring technologies to prevent and fight contamination of their water areas (SDG 14).
- Promote the application of AI to identify deterioration (mainly by desertification and fires) leveraging the processing of satellite images of natural environments, control and reduce their contamination, and ultimately warn about any risks that may threat ocean and land ecosystems (SDG 14, 15).
- Enable real-time monitoring of animal and plant populations on land and below water to preserve balanced ecosystems, identifying threats such as illegal fishing and deforestation (SDG 14, 15).
- Promote the application of AI in agriculture to improve its productivity, thereby reducing water consumption and avoiding deforestation (SDG 15; *also linked to SDG 2, see Figure 8*).

Annex D – Laws, Directives and Regulations on the preservation of government data and digital services with applicable scope in Portugal or in the EU. Source: AMA, 2021

OBJECT	LEGISLATION	SCOPE
Approves the general principles regarding open data and reuse of public sector information	Law No. 68/2021, of August 26; transposes Directive (EU) 2019/1024	PT
Protection with regard to the processing of personal data and on the free movement of such data	Law No. 58/2019 of August 8 - ensures the implementation of Regulation (EU) 2016/679	PT
On open data and the re-use of public sector information (recast)	Directive (EU) 2019/1024 of the European Parliament and of the Council, of June 20, 2019	EU
Establishes copyright and related rights in the digital single market	Directive (EU) 2019/790 of the European Parliament and of the Council of April 17, 2019	EU
Establishes the framework for the free flow of non-personal data in the European Union	Regulation (EU) 2018/1807 of the European Parliament and of the Council of November 14, 2018	EU
Technical guidelines for Public Administration on security architecture of networks and info systems	Resolution of the Council of Ministers No. 41/2018	PT
National Regulation of Digital Interoperability (RNID)	Resolution of the Council of Ministers No. 2/2018	PT
Approves the regime for access to administrative and environmental information and reuse of administrative documents	Law No. 26/2016, of August 22; transposes Directive 2003/4/EC, of the European Parliament and of the Council, of January 28, and Directive 2003/98/EC	PT
General Data Protection Regulation (GDPR)	Regulation (EU) 2016/679 of the European Parliament and of the Council, of April 27, 2016	EU
Establishes the re-use of public sector information	Directive 2013/37/EU of the European Parliament and of the Council, of June 26, 2013	EU
Concerning the processing of personal data and the protection of privacy in the electronic communications sector	Law No. 46/2012, of August 29; transposes Directive No. 2009/136/EC, amends Directive No. 2002/58/EC	PT
Establishes the adoption of open standards in State information systems	Law No. 36/2011, of June 21	PT
Retention of data generated in context of the provision of publicly available electronic communications services or of public communications networks	Ordinance No. 694/2010, of August 16; makes the third amendment to Ordinance No. 469/2009, May 6	PT
Concerning universal service and users' rights relating to electronic communications networks and services, the processing of personal data and the protection of privacy in the electronic communications sector	Directive 2009/136/EC of the European Parliament and of the Council, of November 25, 2009;	EU
Concerning retention of data generated in the context of publicly available electronic communications services or of public communications networks	Directive 2006/24/EC of the European Parliament and of the Council of March 15, 2006	EU
On public access to environmental information	Directive 2003/4/EC of January 28, 2003	EU

Annex E – European Legal Framework on AI (Regulatory Milestones Timeline)

Source: https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence

DATE	REGULATORY MILESTONE TIMELINE (LINKS AVAILABLE)
August 2024	AI Act enters into force
February 2024	European AI Office
January 2024	AI innovation package to support Artificial Intelligence startups and SMEs
December 2023	Political agreement on the AI Act reached by the co-legislators
June 2023	European Parliament's negotiating position on AI Act
December 2022	General approach of the Council on AI Act
September 2022	Proposal for an AI liability directive
June 2022	Launch of first AI regulatory sandbox in Spain: Bringing the AI Regulation forward
December 2021	Committee of the Regions, Opinion on the AI Act European Central Bank, Opinion on the AI Act
November 2021	Council of the EU: SI Presidency compromise text on the AI Act European Economic and Social Committee, Opinion on the AI Act High-Level Conference on AI: From Ambition to Action (3d European AI Alliance Assembly)
June 2021	Public consultation on Civil liability – adapting liability rules to the digital age and artificial intelligence European Commission: Proposal for a Regulation on Product Safety
April 2021	European Commission: Communication on Fostering a European approach to AI European Commission: Proposal for a regulation laying down harmonized rules on AI European Commission: updated coordinated plan on AI European Commission: Impact assessment of an AI regulation
October 2020	2nd European AI Alliance Assembly

July 2020	Inception impact assessment: Ethical and legal requirements on AI High-Level Expert Group on AI: Sectorial recommendations of trustworthy AI High-Level Expert Group on AI: Final assessment list on trustworthy AI (ALTAI)
February 2020	European Commission: White paper on AI: a European approach to excellence and trust Public consultation on a European approach to excellence and trust in AI
December 2019	High-Level Expert Group on AI: Piloting of assessment list of trustworthy AI
June 2019	First European AI Alliance Assembly High-Level Expert Group on AI: Policy and investment recommendations of AI
April 2019	European Commission Communication: Building trust in human-centric artificial intelligence High-Level expert group on AI: Ethics guidelines for trustworthy AI
December 2018	European Commission: Coordinated plan on AI European Commission Communication: AI made in Europe European Commission (Press release): AI made in Europe Stakeholder consultation on draft ethics guidelines for trustworthy AI
June 2018	Launch of the European AI alliance Set up of the high-level expert group on AI
April 2018	Press release: Artificial intelligence for Europe Communication: Artificial intelligence for Europe Declaration of cooperation on artificial intelligence Staff working document: Liability for emerging digital technologies
March 2018	Press release: AI expert group and European AI alliance

Annex F – Research Survey

Link: https://qualtricsxmqyzmskxqt.qualtrics.com/jfe/form/SV_0eO8DpubzbHKdJI

1. INTRODUCTION

ISCTE-IUL Research Survey:
The Role of AI in Environmental Sustainability for the Health & Tech Industry

Thank you for participating in this survey!

The purpose of this survey is to gather insights into your organization's capabilities and practices regarding the use of Artificial Intelligence (AI) in environmental sustainability fields, particularly within the Health & Technological Industry. Your responses will contribute to a thesis research project aimed at understanding how AI can enhance environmental sustainability efforts, applications and solutions.

Your responses to this survey are strictly confidential. All information provided will be used solely for research purposes and will be treated with the utmost confidentiality. Your participation is voluntary, and you may withdraw at any time without providing a reason.

Note: All checkboxes (☐/☒) shown below are of **multiple choice**. Please select all that may apply. You may jump any question or leave blank if not applicable to your organization.

This survey should take approximately 5 to 7 minutes to complete.

1. INTRODUCTION

1.1 - Please indicate your function or position at the organization

Function / Position [ ]

1.2 - Please describe your organization from the following categories

- ☐ Technology or IT Services Provider
- ☐ Healthcare IT or Software Provider
- ☐ Environmental Consultancy Firm
- ☐ Medical Device Manufacturer
- ☐ Pharmaceutical Company
- ☐ Biotechnology Firm
- ☐ Healthcare Provider or Medical Institution
- ☐ Research Institution or Academic Organization
- ☐ Government Agency or Public Sector Organization
- ☐ Non-Governmental Organization (NGO) or Non-Profit Organization
- ☐ [ ] Other (please specify):

2. AI CAPABILITIES AND APPLICATIONS

2.1 - Please select your organization's AI capabilities relevant to environmental sustainability solutions

- ☐ Machine Learning
- ☐ Natural Language Processing
- ☐ Computer Vision
- ☐ Speech Recognition
- ☐ Predictive Analytics
- ☐ [ ] Other (please specify):
- ☐ N/A

2.2 - On a scale from 1 to 5, how effective are your AI capabilities in addressing environmental sustainability challenges? (Fill in according to selection on 2.1)

	1 (Not at all)	2 (Slightly)	3 (Moderately)	4 (Very)	5 (Extremely)
Machine Learning	○	○	○	○	○
Natural Language Processing	○	○	○	○	○
Computer Vision	○	○	○	○	○
Speech Recognition	○	○	○	○	○
Predictive Analysis	○	○	○	○	○
Other capability specified on question 2.1	○	○	○	○	○

2.3 - How does your organization apply AI specifically in the context of environmental sustainability?

- ☐ Data Collection and Analysis
- ☐ Environmental Impact Assessment
- ☐ Environmental Predictive Modeling
- ☐ Waste Management
- ☐ Energy Resource Optimization
- ☐ Emission Reduction Strategies
- ☐ Biodiversity Monitoring
- ☐ Regulatory Compliance and Reporting
- ☐ Sustainable Supply Chain Management
- ☐ Remote Monitoring & Telehealth Solutions
- ☐ Green Innovation in R&D
- ☐ ______ Other (please specify):
- ☐ N/A

2.4 - On a scale from 1 to 5, how effective are your AI applications in addressing environmental sustainability challenges? (Fill in according to selection on 2.3)

	1 (Not at all)	2 (Slightly)	3 (Moderately)	4 (Very)	5 (Extremely)
Data Collection and Analysis	○	○	○	○	○
Environmental Impact Assessment	○	○	○	○	○
Environmental Predictive Modeling	○	○	○	○	○
Waste Management	○	○	○	○	○
Energy Resource Optimization	○	○	○	○	○
Emission Reduction Strategies	○	○	○	○	○
Biodiversity Monitoring	○	○	○	○	○
Regulatory Compliance and Reporting	○	○	○	○	○
Sustainable Supply Chain Management	○	○	○	○	○
Remote Monitoring & Telehealth Solutions	○	○	○	○	○
Green Innovation in R&D	○	○	○	○	○
Other application specified in question 2.3	○	○	○	○	○

3. DATA COLLECTION, ANALYSIS AND RESULTS

3.1 - How does your organization collect and process data related to GHG emissions or other sustainability metrics?

- ☐ Automated Sensors and IoT Devices
- ☐ Satellite Imagery and Remote Sensing
- ☐ Data Integration from Operational Systems
- ☐ AI-Powered Data Analytics Platforms
- ☐ Manual Data Collection and Reporting
- ☐ Blockchain for Data Transparency or Traceability
- ☐ Collaboration with 3rd Party Data Providers
- ☐ Other (please specify): ____________
- ☐ N/A

3.2 - On a scale from 1 to 5, how effective are your AI-driven data collection and analysis solutions? (Fill in according to selection on 3.1)

	1 (Not at all)	2 (Slightly)	(Moderately)	4 (Very)	(Extremely)
Automated Sensors and IoT Devices	○	○	○	○	○
Satellite Imagery and Remote Sensing	○	○	○	○	○
Data Integration from Operational Systems	○	○	○	○	○
AI-Powered Data Analytics Platforms	○	○	○	○	○
Manual Data Collection and Reporting	○	○	○	○	○
Blockchain for Data Transparency or Traceability	○	○	○	○	○
Collaboration with 3rd Party Data Providers	○	○	○	○	○
Other solution specified on question 3.1	○	○	○	○	○

4. CLIENT SUPPORT, IMPACT AND CASE STUDIES

4.1 - How do you assist your clients to improve environmental sustainability outcomes, while leveraging AI-based solutions?

- ☐ Data-driven Consulting Services
- ☐ Real-time Environmental Monitoring
- ☐ Carbon Footprint Analysis and Reduction Strategies
- ☐ Regulatory Compliance and Reporting
- ☐ AI-based Predictive Maintenance for Sustainability
- ☐ Training, Education and Capacity Building
- ☐ Optimization of Resource Management
- ☐ Other (please specify): ____________
- ☐ N/A

4.2 - Please rate the effectiveness of your client support AI-based solutions or services (Fill in according to selection on 4.1)

	1 (Not at all)	2 (Slightly)	3 (Neutrally)	4 (Very)	5 (Extremely)
Data-driven Consulting Services	○	○	○	○	○
Real-time Environmental Monitoring	○	○	○	○	○
Carbon Footprint Analysis and Reduction Strategies	○	○	○	○	○
Regulatory Compliance and Reporting	○	○	○	○	○
AI-based Predictive Maintenance for Sustainability	○	○	○	○	○
Training, Education and Capacity Building	○	○	○	○	○
Optimization of Resource Management	○	○	○	○	○
Other solution specified on question 4.1	○	○	○	○	○

4.3 - On average, what percentage in the following trends have your clients been able to achieve while applying your AI solutions?

Note: On a scale from 0 to 100%, select only the applicable ones.

	0	10	20	30	40	50	60	70	80	90	100	
GHG Emissions Reduction												
Waste Production Reduction												
Renewable Energy Integration												
Recycling Rates												
Biodiversity Conservation												
Community Engagement and Social Impact												

4.4 - Have your AI solutions been implemented successfully in any health or tech company?

- Yes
- No
- N/A

5. CHALLENGES AND FUTURE DIRECTION

5.1 - What are the primary challenges your organization faces while implementing AI-based solutions in environmental sustainability?

- ☐ Lack of Trust or Confidence in AI
- ☐ Data Quality, Integrity or Availability
- ☐ Regulatory Compliance
- ☐ Cost of Implementation
- ☐ Skill Gap in Workforce
- ☐ Other (please specify):
- ☐ N/A

5.2 - How do you envision the future role of AI in the health and tech industry?

- ☐ Enhancing Efficiency of Sustainability Practices
- ☐ Scaling Sustainability Solutions
- ☐ Addressing Emerging Environmental Risks
- ☐ Ethical AI Use and Governance
- ☐ Other (please specify):
- ☐ N/A

5.3 - In your opinion, how many years until AI technologies can significantly impact the overall industry sustainability practices?

- ◯ Less than 1 year
- ◯ 1 to 5 years
- ◯ 5 to 10 years
- ◯ 10 to 20 years
- ◯ More than 20 years

6. ADDITIONAL COMMENTS

6.1 - Is there any additional information or insights you would like to share regarding your organization's approach to using AI for environmental sustainability?

Note: If you do not wish to provide any additional info, please type N/A.

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