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Τίτλος Διπλωματικής

“Πράσινη Τεχνητή Νοημοσύνη: Ανάλυση των
πρακτικών υιοθέτησης και των πολιτικών για
βιώσιμη διακυβέρνηση”

[Ευαγγελία Αλεξοπούλου]

[Α.Μ.: 3262023001 , icsdm623001@icsd.aegean.gr]

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Η ΤΡΙΜΕΛΗΣ ΕΠΙΤΡΟΠΗ ΔΙΔΑΣΚΟΝΤΩΝ
ΕΠΙΚΥΡΩΝΕΙ ΤΗ ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ

ΤΗΣ ΕΥΑΓΓΕΛΙΑΣ ΑΛΕΞΟΠΟΥΛΟΥ

Μέλη επιτροπής

Επιβλέπων ΧΑΡΑΛΑΜΠΟΣ ΑΛΕΞΟΠΟΥΛΟΣ,
Βαθμίδα: Αναπλ. Καθηγητής

2^ο μέλος Καθ. Ι. ΧΑΡΑΛΑΜΠΙΔΗΣ
3^ο μέλος Καθ. Ε. ΛΟΥΚΗΣ

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ΟΝΟΜΑΤΕΠΩΝΥΜΟ

Πανεπιστήμιο Αιγαίου

Πρόλογος

Η παρούσα διπλωματική εργασία εκπονήθηκε στο πλαίσιο του Μεταπτυχιακού Προγράμματος Σπουδών με τίτλο «Ηλεκτρονική Διακυβέρνηση» του Πανεπιστημίου Αιγαίου και αφορά στην αντιμετώπιση του ενεργειακού αποτυπώματος και της μείωσης εκπομπών CO₂ στην εποχή της ραγδαίας εξέλιξης της ΤΝ και της αύξησης υπολογιστικής ισχύος των συστημάτων της ΤΝ αλλά και της (Γεν) ΤΝ. Το θέμα αφορά στην διερεύνηση των πρακτικών υιοθέτησης της Πράσινης Τεχνητής Νοημοσύνης (Green AI) και των πολιτικών για βιώσιμη διακυβέρνηση.

Η επιλογή του θέματος έγινε λόγω της αυξημένης ανάγκης των ενεργειακών απαιτήσεων και αυξημένης υπολογιστικής ισχύος για την λειτουργία των υπολογιστικών υποδομών για την εκτέλεση των μοντέλων της ΤΝ.

Θα ήθελα να εκφράσω τις θερμές μου ευχαριστίες στον επιβλέποντα καθηγητή μου, κ. Χάρη Αλεξόπουλο, για την καθοδήγηση και την υποστήριξή του καθ' όλη την διάρκεια της εκπόνησης της έρευνάς μου αλλά και για την κατανόηση που είχε σε διάφορα θέματα και συγκυρίες που παρουσιάστηκαν κατά την διάρκεια εκπόνησης της μελέτης. Επίσης θα ήθελα να ευχαριστήσω όλους τους εμπειρογνώμονες που συμμετείχαν στις ημι-δομημένες συνεντεύξεις, των οποίων η συνεισφορά ήταν πολύτιμη και συνέβαλε στα εμπειρικά ευρήματα της μελέτης και στην εκτέλεση/ολοκλήρωση της έρευνάς μου.

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Αφιερωμένη

....στον πατέρα μου που μου δίδαξε να μην τα παρατάω ποτέ!!

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Θα εξεταστούν κριτικά οι πρακτικές υιοθέτησης πράσινης ΤΝ και θα αναπτυχθεί ένα υπεύθυνο πλαίσιο υιοθέτησης πράσινης ΤΝ για την ανάπτυξη αντίστοιχης πολιτικής. Θα ακολουθήσει μια επισκόπηση πολιτικής και κανονιστικών ρυθμίσεων και ένα πρακτικό πλαίσιο με βάση τις φάσεις του κύκλου ζωής της ΤΝ για την αποτελεσματική υπεύθυνη ανάπτυξη της πράσινης ΤΝ, αντιμετωπίζοντας την επείγουσα ανάγκη για βιώσιμη διακυβέρνηση της ΤΝ, όπως προκύπτει από το γεγονός ότι η (Γεν)ΤΝ γίνεται πυλώνας της ψηφιακής διακυβέρνησης, με αυξημένο περιβαλλοντικό αποτύπωμα της ΤΝ και τα εκτεθειμένα κενά στην ετοιμότητα και τη ρυθμιστική ευθυγράμμιση. Σκοπός της εργασίας είναι η κριτική εξέταση των πρακτικών υιοθέτησης της Πράσινης ΤΝ και η ανάπτυξη ενός υπεύθυνου πλαισίου υιοθέτησης της Πράσινης ΤΝ, προκειμένου να ενημερωθεί η αντίστοιχη ανάπτυξη πολιτικών. Η μελέτη θα χρησιμοποιήσει ένα ερευνητικό σχέδιο πολλαπλών μεθόδων που περιλαμβάνει τρεις συμπληρωματικές φάσεις. Ξεκινά με την ανάλυση του ρυθμιστικού πλαισίου και βιβλιογραφίας, όπου θα πραγματοποιηθεί κριτική εξέταση της πολιτικής και των ρυθμιστικών μέσων της Ευρωπαϊκής Ένωσης, προκειμένου να τεθεί σε πλαίσιο το τοπικό διακυβέρνησης που περιβάλλει την Πράσινη Τεχνητή Νοημοσύνη, αυτό θα συμπληρωθεί από μια συστηματική ανασκόπηση της βιβλιογραφίας, με σκοπό τη σύνθεση των υφιστάμενων ακαδημαϊκών και πολιτικών γνώσεων σχετικά με την υιοθέτηση της πράσινης τεχνητής νοημοσύνης, τον εντοπισμό εννοιολογικών κενών και των αναδυόμενων τάσεων. Το δεύτερο βήμα θα είναι η διερεύνηση της πράσινης τεχνητής νοημοσύνης σε μεγαλύτερο βάθος, μέσω διαβουλεύσεων με εμπειρογνώμονες στον τομέα της έρευνας και ανάπτυξης της τεχνητής νοημοσύνης. Οι πληροφορίες θα συλλεχθούν μέσω συμπλήρωσης ερωτηματολογίου με αυτούς τους βασικούς πληροφοριοδότες. Η σύνθεση του ερωτηματολογίου θα βασίζεται σε καθιερωμένα θεωρητικά μοντέλα υιοθέτησης τεχνολογίας, όπως το πλαίσιο Τεχνολογία-Οργάνωση-Περιβάλλον (TOE) και η Θεωρία Αντίστασης στην Καινοτομία, σύμφωνα με τις αρχές Περιβαλλοντικής, Κοινωνικής και Διακυβέρνησης (ESG), προκειμένου να διασφαλιστεί η θεωρητική συνοχή και το αναλυτικό βάθος. Τα αποτελέσματα των προηγούμενων φάσεων θα καθοδηγήσουν την ανάπτυξη ενός

δομημένου πλαισίου υιοθέτησης της πράσινης τεχνητής νοημοσύνης, το οποίο θα εξεταστεί και θα επικυρωθεί από εμπειρογνώμονες, προκειμένου να διασφαλιστεί ότι είναι σχετικό, εφαρμόσιμο και μεθοδολογικά άρτιο. Η διαδικασία θα ολοκληρωθεί με τεκμηριωμένες συστάσεις για τους υπεύθυνους χάραξης πολιτικής, καθώς και για τους επαγγελματίες. Μέσω της συντονισμένης ανάλυσης πολιτικής, της εμπειρικής έρευνας και της θεωρητικής σύνθεσης, η μελέτη μας στοχεύει στην προώθηση της κατανόησης της ακαδημαϊκής κοινότητας σχετικά με την άνοδο των διαδικασιών υιοθέτησης της πράσινης τεχνητής νοημοσύνης και στην υποστήριξη της ανάπτυξης συνεκτικής στρατηγικής και καλών πρακτικών.

Keywords: *(Green AI, Sustainable AI, Energy-efficient ML, policy regulations, AI Act)*

Abstract

Green AI adoption practices will be examined critically assessed, and a responsible framework for green AI adoption will be developed for policy development. Subsequently, a review of policy and regulatory frameworks and a systematic review of the research literature on the factors and issues of green AI adoption based on the phases of the new technology life cycle will be conducted with the aim of effective and responsible development of green artificial intelligence. There is an urgent need to address sustainable governance of artificial intelligence, as evidenced by the fact that (general) information technology is becoming a pillar of digital governance, with an increased environmental footprint of information technology and apparent gaps in preparedness and regulatory alignment.

The purpose of the work is to critically examine Green AI adoption practices and develop a responsible Green AI-adoption framework to inform respective policy development. The study will employ a multi-method research design comprising three complementary phases. It starts with Policy and Literature Analysis of a critical examination of European Union policy and regulatory instruments that will be conducted to contextualize the governance landscape surrounding Green Artificial Intelligence (Green AI). This will be complemented by a systematic literature review to synthesize existing academic and policy-oriented knowledge on Green AI adoption, identifying conceptual gaps and emergent trends. The second step will be to investigate Green AI practice in greater depth by consulting experts in Artificial Intelligence research and development, as well as researchers and practitioners of AI innovation. Information will be gathered through semi-structured interviews with these key experts. The questionnaire will be based on established theoretical models of technology adoption, such as Technology–Organization–Environment (TOE) framework, Innovation Resistance Theory (IRT) and Institutional Theory to Environmental, Social and Governance (ESG) principles, to guarantee theoretical coherence and analytical depth. Results of the earlier phases will guide the development of a structured green AI adoption framework. The process will end with evidence-based recommendations for policymakers as well as practitioners. Through the concerted policy analysis, empirical research and theoretical synthesis, our study

«Towards Green AI adoption and policy for sustainable AI governance»

aims to advance the understanding of academic community around the rise of Green AI adoption processes and to underpin coherent EU-wide strategy development and good practice

Keywords: *(Green AI, Sustainable AI, Energy-efficient ML, policy regulations, AI Act)*

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1. Introduction

1.1 The Framework of the Thesis

AI's advancement at an unprecedented pace has caused great technological and social changes. Similarly, the introduction of AI has raised several important issues relating to the natural environment and human ethics. As AI will continue to shape much of our future lives, so will the increasing use of generative AI technologies, e.g., GenAI and therefore the energy consumption and compute requirements of AI are rapidly growing (Strubell et al., 2019; Henderson et al., 2020). Thus, the need for a sustainable or "green" AI approach has become urgent. Emphasis must be placed on developing and deploying AI in an environmentally responsible way (Schwartz et al., 2019; Verdecchia et al., 2023; UNESCO, 2021).

The growing recognition of the impact of AI on the environment has not yet resulted in adequate development of policies and regulations that address the implementation of AI. There remain significant gaps in both the development of policies and the regulatory coherence necessary to achieve successful implementation of AI (Jobin et al., 2019; European Commission, 2021). One example of this gap can be seen in Europe, where the goal of sustainable development has been closely linked to the digital transformation (European Commission, 2020; Floridi & Cowls, 2021; UNESCO, 2021). There is an urgent need for the European Union to develop a comprehensive approach to developing and implementing sustainable and ethical governance of technology in alignment with a data-and-evidence-based approach. By creating this alignment, it will be possible to create an environment where both digital and green transitions can be viewed as being part of a larger vision of responsible innovation by the European Union.

This thesis falls within the field of digital governance and innovation policy, while highlighting an important research gap concerning the use and integration of "green artificial intelligence" in organizations (European Commission, 2020; Floridi & Cowls, 2021; Verdecchia et al., 2023). The main purpose of the research is to develop the Green AI Adoption Framework, a coherent and holistic framework based on empirical data and theoretical evidence, which aims to support and optimize the decision-making process regarding the development of sustainable artificial intelligence

applications at the European Union and Member State level (Schwartz et al., 2019; UNESCO, 2021). The contribution of the research to the existing body of knowledge is strengthened using multiple methods: policy and systematic literature review, collection of qualitative primary data through semi-structured interviews with practitioners and experts in the field, and synthesis of findings through theoretical frameworks associated with technology adoption. The theoretical frameworks are the Technology–Organization–Environment (TOE) framework proposed by Tornatzky & Fleischer (1990), the Innovation Resistance Theory (IRT) proposed by Ram & Sheth (1989) and the Theory of Institutions proposed by DiMaggio & Powell (1983) in combination with the Environmental Social Governance (ESG) principles (Eccles et al., 2014; Kotsantonis et al., 2016). Through this multi-level approach, it is possible to develop an empirically valid and scientifically useful tool to assist policymakers with the responsible sustainable and ethical adoption of artificial intelligence technologies (Jobin et al., 2019; European Commission, 2021).

The main goal of this study is to investigate and analyse the key influences, barriers, and challenge forces in adopting Green Artificial Intelligence (AI) Technology in Greece and across Europe, by way of technology, organisation, and environment. Through an analysis of the interplay among drivers, barriers, and regulatory framework(s), the research will provide useful knowledge about how institutional/policy/innovation dynamics create and support sustainable AI practices. In support of this goal, the research will answer the primary research question: **What factors—drivers, barriers, and regulatory frameworks—shape the adoption of Green Artificial Intelligence (Green AI) across organizational, technological, and environmental dimensions, and how can these insights guide the development of sustainable practices of adoption of Green AI policy and governance within Greece?**

To answer the broader research question, the study focuses on the following sub-questions:

1. **Technological Dimension – Drivers and Barriers:** What technological factors (e.g., computational efficiency, data availability, infrastructure, and innovation capacity) facilitate or constrain the adoption of Green AI practices within Greece?
2. **Organizational Dimension – Strategic and Cultural Influences:** How do organizational capabilities, leadership commitment, financial resources, and

internal sustainability cultures influence the integration of Green AI principles into operational and decision-making processes?

3. Environmental and Institutional Dimension – Policy and Governance Contexts:

How do European Union regulatory frameworks, national policy instruments, and institutional pressures shape the pace and direction of Green AI adoption?

4. Integration and Policy Implications: How can the insights derived from these dimensions inform the design of effective policy frameworks and governance mechanisms that promote sustainable AI deployment in line with EU sustainability objectives?

Through these interlinked questions, the research aims to generate a comprehensive, empirically grounded framework that bridges the gap between sustainability objectives and AI innovation policy, thereby contributing to both academic scholarship and evidence-based policymaking in the European context.

1.2 Aim of the Thesis

The aim of this thesis is to critically assess contemporary practices, forces driving adoption, as well as challenges encountered in embracing Green Artificial Intelligence (Green AI), thus aiming to create a comprehensive, responsible, and context-adapted framework for embracing Green AI adoption (Schwartz et al., 2019; Verdecchia et al., 2023; UNESCO, 2021). Such a framework shall be developed on strong theoretical foundations by applying proven technological adoption theories (Tornatzky & Fleischer, 1990; Ram & Sheth, 1989) and theories of sustainability governance (Floridi & Cowls, 2021; Eccles et al., 2014; Kotsantonis et al., 2016), so as to be empirically validated by applying methods of qualitative research (Creswell & Poth, 2018; Patton, 2015) to examine views from key stakeholders. Toward achieving a balanced application of insights from research study and analysis of policies to develop evidence-based policies for embracing technological adoption regulations on a European (European Commission, 2020, 2021, 2022) and on a state-level basis (Floridi et al., 2019), aiming to contribute to enhancing AI-based ecosystems on a sustainability-oriented (Floridi et al., 2019; Floridi & Cowls, 2021) basis.

All the three above-mentioned subordinate questions directly fall under the overarching aim. Each sub-question will examine a different aspect or level of the

development of the framework. The examination of technological drivers and barriers, Sub-question 1 investigates the infrastructural and innovation-related conditions that will enhance the deployment of Green AI. This is based on the works of such authors as Strubell et al. (2019) and Henderson et al. (2020). Sub-question 2 deals with organizational influences and captures how internal governance structures, leadership, and resource allocation influence the process of adoption. This has its background from Eccles et al. (2014) and Kotsantonis et al. (2016). Environmental and institutional dimensions are the scope of Sub-question 3, which covers the wider policy, regulatory, and normative contexts in which AI systems operate, thereby locating the role of European and national governance frameworks. This falls in line with European Commission (2020, 2021) and UNESCO (2021). The integration and policy implication dimension, captured in Sub-question 4, synthesizes findings across all levels and provides actionable recommendations in terms of responsible and sustainable AI governance. This has been argued by Floridi & Cowls (2021) and Jobin et al. (2019).

Together, these sub-questions operationalize the thesis aim by linking theoretical perspectives with empirical realities, ensuring that the resulting Green AI adoption framework is both academically rigorous and practically relevant (Tornatzky & Fleischer, 1990; Ram & Sheth, 1989). This alignment ensures that the study not only contributes to scholarly debates on digital sustainability and governance but also provides policy-relevant insights that can guide the European Union's ongoing efforts toward a responsible and green digital transformation (European Commission, 2020; European Commission, 2021; UNESCO, 2021).

1.3 Scope of the Thesis

To achieve the stated objective, the research will be organized into a sequence of interrelated stages ensuring both theoretical soundness and empirical validity. Initially, a **Systematic Literature Review (SLR)** will be performed, to synthesize the body of knowledge on the adoption structures for Green AI, the assessment of environment footprints, and sustainability issues throughout the life cycle of Artificial Intelligence (Verdecchia et al., 2023; Strubell et al., 2019; Henderson et al., 2020;

Schwartz et al., 2019). This phase will provide a sound theoretical basis for interpreting the role that technological, organization, and sustainability issues play in the adoption process for Green AI (Tornatzky & Fleischer, 1990).

Afterwards, a comprehensive **review of key European Union policy and regulatory frameworks**—including the *Artificial Intelligence Act* (European Commission, 2021), the *Corporate Sustainability Due Diligence Directive* (European Commission, 2022), and the *Critical Raw Materials Act* (European Commission, 2023) and others will be undertaken to identify potential overlaps, inconsistencies, and gaps in the regulation of AI's environmental impact (Floridi & Cowls, 2021; Jobin et al., 2019).

The **empirical research** will utilize semi-structured interviews with experts from the academic, public, and industrial sectors of Greece with the intention of deriving rich insights into best practices, factors inspiring, and factors impeding the adoption of Green AI (Creswell & Poth, 2018). This method enables the collection of rich data that can beneficially facilitate research into the multifaceted factors outlined by the theoretical frameworks, namely Technology-Organizations-Environment (TOE) model (Tornatzky & Fleischer, 1990), Innovation Resistance Theory (Ram & Sheth, 1989), and principles of Environmental, Social, and Governance (Kotsantonis et al., 2016; Eccles et al., 2014).

Building on these findings, the research will examine/develop a **Green AI adoption framework** that integrates these theoretical foundations to explain and guide sustainable green AI practices implementation.

Finally, the study will culminate in the formulation of **evidence-based policy recommendations** designed to support policymakers and practitioners in advancing sustainable AI governance in alignment with the European Union's overarching sustainability objectives (European Commission, 2020; UNESCO, 2021).

1.4 Structure of the Thesis

The structure of this thesis is organized into five principal chapters, each addressing a distinct component of the research process. Chapter 1 – Introduction provides an overview of the study, outlining its context, objectives, scope, and overall structure.

Chapter 2 – Theoretical background and conceptual framework, and reference to the existing literature. Chapter 3 – Research Methodology describes the research design and methodological approach adopted in the study. It elaborates on the theoretical underpinnings, including the Technology–Organization–Environment (TOE) framework, the Innovation Resistance Theory (IRT) and the Institutional Theory as well as the design of the semi-structured interviews and the data collection procedures. Chapter 4 –presents the findings of the SLR and a detailed analysis of relevant European Union policies and legislative frameworks pertaining to Green Artificial Intelligence (Green AI) and sustainable digital governance, the empirical results derived from the interviews, the Synthesis of the findings and the development process of the proposed Green AI adoption framework. Chapter 5 – Conclusions and Policy Recommendations synthesize the key findings of the study and formulates evidence-based policy and practical recommendations aimed at promoting, sustainable, and ethically aligned adoption of Green AI across the European Union.

2. Background and Conceptual Framework

2.1 Definitions and Conceptualizations of “Green AI”

Artificial Intelligence (AI) stands as a revolutionary force in the world economy; it boosts productivity and innovation in all spheres. However, its increasing computational requirements and environmental impact have led to increasing concerns regarding its sustainability. The new model of ‘Green AI’ focuses on making the development and use of AI more efficient in the environment as well as more ethical in governance (Verdecchia et al., 2023; Clemm et al., 2024). The increasing transition to sustainable digitalization indicates that Green AI is no longer a technology issue, it also stands as an important governance agenda (Raman et al., 2024). The adoption of Green AI in this study stands as multi-dimensional theoretical development in which Technology-Organization-Environment (TOE) Theory, Innovation Resistance Theory (IRT), and Institutional Theory are combined.

The idea of "Green Artificial Intelligence" (Green AI) emerged as people became more conscious of the significant energy and environmental costs associated with AI, even though it promotes innovation. Academics define "green AI" as the development and

application of AI technologies that minimize their detrimental effects on the environment, optimize energy efficiency, and promote sustainable societal goals (Tabbakh, A., 2024). Ul Haq et al. (2025) frame green AI as a strategic enabler for sustainable performance in small and medium-sized enterprises (SMEs), emphasizing its capacity to achieve a balance between technological advancement and environmental stewardship. Here, Green AI is not only a tool for operational efficiency but is also positioned to achieve long-term sustainability outcomes through green investment and leadership mechanisms. Azhar et al. (2025) extend this view, describing Green AI as an organizational capability that integrates artificial intelligence adoption with green human resource management and green innovation, enhancing both environmental and business performance. Their perspective underscores Green AI's role in mediating sustainability through human, technological, and cultural factors.

Weng (2025) links AI innovation to corporate environmental responsibility by interpreting Green AI as a technological mechanism for improving ESG (Environmental, Social, and Governance) performance. In this way, Green AI is viewed as a tool for sustainable value creation as well as a productivity booster.

One of the most important formal definitions of Green AI is given by Verdecchia et al. (2023), who define it as "a paradigm aimed at reducing the carbon and energy footprint of AI systems without compromising performance or fairness." They set it apart from "Red AI," which puts performance ahead of environmental costs. Standardized energy and carbon efficiency metrics are essential for the entire AI lifecycle, according to their review.

According to Clemm et al. (2024), Green AI is a multidisciplinary field that combines AI engineering, computational efficiency, and sustainability science. They support the integration of transparent lifecycle accounting, lightweight model architecture, and carbon-aware training as essential design principles.

Green AI is defined by Yu et al. (2025) in terms of green governance performance, with a focus on how it promotes environmental compliance, sustainable corporate policies, and green competitiveness. Their research places the adoption of Green AI within governance frameworks that are influenced by normative and regulatory forces.

The technical aspect of Green AI is the focus of Tabbakh et al. (2024) and Barbierato & Gatti (2024), who present it as a general idea for eco-efficient algorithm design, hardware optimization, and data management that together lower the computational and energy intensity of AI workloads.

Finally, Alzoubi et al. (2025) expand the scope of Green AI to sectoral applications such as healthcare, defining it as the use of sustainable AI algorithms and techniques that improve diagnostic and operational efficiency while minimizing resource consumption.

Green AI emerges as both: (1) a **technological paradigm**—focused on reducing the energy, carbon, and computational costs of AI systems, and (2) a **governance and policy paradigm**—embedding sustainability principles into AI regulation, strategy, and ethical accountability (Bolón-Canedo, V., Morán-Fernández, L., Cancelas, B., et al. 2022/2023).

The most widely accepted definition, synthesizing these perspectives, can be stated as: **Green AI** is the practice of designing, developing, and applying artificial intelligence systems that maximize social and economic value while minimizing environmental impact through energy-efficient architectures, responsible data use, and governance mechanisms that ensure sustainability and transparency across the AI lifecycle (Schwartz et al. (2020); Bolón-Canedo et al. (2023)).

The literature defines “Green AI” as “the response to ‘Red AI’ approaches that are even more resource-hungry, in which computation efficiency is less prioritized and resources are less optimized.” Different authors addressed this issue in their most recent publications, such as Barbierato & Gatti in 2024, and Verdecchia et al. in 2023. Thus, Green AI is defined as “the paradigm committed to making AI systems more sustainable in their lifecycle, with a focus on energy efficiency, resource optimization, and CO₂ emissions reduction.” It is, of course, one of those topics that eminently captures the message of change conveyed by the adopted UN Sustainable Development Goals, specifically goals 7: Affordable and Clean Energy, 11: Sustainable Cities and Communities, and 13: Climate Action. (OK)

While AI has become a key enabler of digital transformation for both the public and private sectors, offering great opportunities to enhance efficiency, innovation, and data-driven decision-making, such AI technologies have grown increasingly

sophisticated, and their environmental footprint, rooted in data-intensive computation, high energy consumption, and hardware production, is now emerging as a major global concern (Strubell et al. (2019), Schwartz et al. (2020), Wu et al. (2022).

The definition of Green AI underlines the development and usage of AI systems that are energy-efficient, resource-aware, and sustainable. It encourages reducing the computational and carbon costs associated with AI across its whole lifecycle: from data collection to model training, deployment, and maintenance (Bolón-Canedo, V., Morán-Fernández, L., Cancelas, B., et al., 2023). As seen in Henderson et al. (2020), Patterson et al. (2021), and Zhou et al. (2023), this can be done in the private sector to reinforce corporate sustainability strategies and enable more operational efficiency or, in the public sector, to reinforce climate-neutrality objectives and pursue sustainable digital governance.

In the public sector, Green AI acts as an enabler of sustainable digital transformation. There is a growing consciousness on the part of governments that technological innovation needs to be in conjunction with green transition goals, as emphasized in the Green Digital Transformation of Public Administration (European Commission, 2023). By integrating energy-efficient, ethically governed, and socially inclusive AI systems, public administrations can lower operational emissions, increase transparency, and strengthen public trust in digital governance. Embedding environmental criteria within AI procurement and policy frameworks enables governments to act as exemplary adopters of sustainable innovation, such as through *Green Public Procurement (GPP)* policies. Such initiatives as green public procurement, AI carbon reporting, and open environmental data platforms can further institutionalize sustainability principles within general public-sector operations. In developing such practices, governments diminish the environmental impact of AI adoption while enhancing administrative capacity for data-driven sustainability monitoring and policy evaluation.

2.2 Theoretical framing

The exponential growth in Artificial Intelligence technologies has created enormous social and economic benefits but at considerable environmental costs (Bolón-Canedo, V., Morán-Fernández, L., Cancelas, B., et al., 2023). Since AI models, particularly deep learning architectures, demand huge computational resources, their energy consumption and carbon footprint have become an emerging concern. This gives rise to the new concept of Green AI: the development and use of AI systems that are not only energy-efficient but also environmentally sustainable. According to Schwartz et al. (2020) and Strubell et al. (2019), Green AI emphasizes the optimization of algorithmic performance with minimal environmental impact and aligns technological innovation with sustainability objectives.

Green artificial intelligence emphasizes the responsible use of artificial intelligence to minimize energy consumption and carbon dioxide emissions, while enabling the development of sustainability-oriented applications. Recent literature distinguishes between "Green-by-Design" (green from the design stage) — reducing the environmental cost of artificial intelligence itself — and "Green-via-AI" (green through artificial intelligence) —using artificial intelligence to achieve sustainability outcomes (Verdecchia et al., 2023; Clemm et al., 2024; Weng et al., 2025). For businesses and SMEs, integrating artificial intelligence and sustainability goals enhances eco-efficiency, optimizes processes, and boosts ESG performance (ul Haq et al., 2025; Azhar et al., 2025). However, achieving these outcomes requires alignment between technological innovation, organizational capacity, and regulatory frameworks.

Understanding the adoption of Green AI requires an examination not only of technological and organizational preparedness but also of the external institutional pressures that guide responsible innovation. Three theoretical perspectives are particularly applicable to explain this multidimensional process: the Technology-Organization-Environment framework-TOE (Tornatzky & Fleischer, 1990), Innovation Resistance Theory – IRT (Ram, S., & Sheth, J. N., 1989) and Institutional Theory (DiMaggio & Powell, 1983; Scott, 2014). Together, these frameworks provide a holistic lens for analyzing how internal capabilities and the pressures of external legitimacy interact to drive sustainable AI adoption.

2.2.1 The Technology–Organization–Environment Framework

The TOE framework, as proposed by Tornatzky and Fleischer (1990), focuses on technology adoption in the light of three contextual dimensions: Technology, Organization, and Environment. This has widely been applied to study how technological innovations are adopted within firms, in information system research (Oliveira & Martins, 2011). In the case of Green AI, a systematic search for such factors as technological readiness, internal resources, and external policy or market pressures can be explored through a TOE framework.

The technological context is about the characteristics of the technologies available to the organization, including perceived benefits, complexity, compatibility, and readiness. For Green AI, these technologies include energy-efficient algorithms, carbon-tracking tools, data infrastructure, among others (Strubell et al., 2019; Lacoste et al., 2023). The Organizational context involves leadership commitment, resources, skills, and the readiness of the firm's culture to embed the goals of sustainability into AI strategies. The Environmental context refers to a set of external factors such as regulations, industry competition, and market or societal expectations regarding sustainable and ethical AI practices (Tornatzky & Fleischer, 1990).

The Technology–Organization–Environment (TOE) framework suggests that organizational technology adoption is shaped by technological attributes, organizational conditions, and the surrounding external environment (Kalmus & Nikiforova, 2024). Although such models are effective in explaining the drivers of technology acceptance, they place less emphasis on the obstacles that hinder adoption. A comprehensive understanding of technology integration requires examining both enabling factors and sources of resistance.

2.2.2 Innovation Resistance Theory

Innovation Resistance Theory (IRT) addresses this gap by focusing on the barriers and resistance factors that are largely overlooked by the TOE framework (Kalmus & Nikiforova, 2024). IRT seeks to explain how consumers and organizations respond to innovations and why certain innovations encounter resistance (Kalmus & Nikiforova, 2024). According to Ram, resistance is a natural reaction to change, and innovations

that effectively address the sources of resistance are more likely to be successfully adopted (as cited in Kalmus & Nikiforova, 2024). The theory distinguishes between functional and psychological barriers: functional barriers relate to perceived value, usage patterns, and risk, whereas psychological barriers stem from traditions, social norms, and individual perceptions (Kalmus & Nikiforova, 2024).

According to IRT, innovation resistance is influenced by three primary categories of factors: (1) perceived characteristics of the innovation, (2) characteristics of the consumer or organization, and (3) attributes of the diffusion or propagation mechanisms. Originating in business and marketing research, IRT differs from previously discussed models by emphasizing the reasons why organizations or consumers reject technologies rather than adopt them (Kalmus & Nikiforova, 2024).

In the context of Green AI, IRT helps explain organizational hesitation by identifying functional barriers such as complexity and performance risk, psychological barriers including tradition and image concerns, and economic barriers, particularly relevant in emerging fields like Green AI. Consequently, IRT complements the TOE framework by adding a critical perspective on adoption inhibitors, offering deeper insights despite some overlap between the two approaches.

2.2.3 Institutional Theory

In the institutional theory, population follows the rules and regulations of the institutional system to attain legitimacy. The types of Institutional Pressure are Coercive Pressure, Normative Pressure, and Mimetic Pressure. These are classified by DiMaggio and Powell (1983) and also by Scott in the Year 2014: Coercive Pressure arises from formal rules and regulations or government directives (European Union Regulation on Artificial Intelligence Guidelines and Sustainability Guidelines), Normative Pressure arises from professional standards or even the ethical guidelines set by the public (ESG Disclosure) and Mimetic pressure emerges when organizations or societies imitate the practices of competitors or peers in order to preserve competitiveness or enhance legitimacy.

In the context of Green AI, institutional forces press organizations to adopt sustainable AI practices not only for efficiency but also for legitimacy and compliance. Coercive

pressures force alignment with policy, normative pressures promote adoption of shared ethical standards and mimetic pressures drive imitation of leading sustainable AI practices, hence reinforcing the institutionalization of sustainability within AI development.

In fact, the theoretical foundation underpinning this study and leading to the formulation of the research question, "What factors-drivers, barriers, and regulatory frameworks, shape the adoption of Green AI across organizational, technological, and environmental dimensions, and how can these insights guide the development of responsible practices of adoption of Green AI policy and governance within the European Union?", is based on several interrelated theoretical frameworks and models. It is the combination of knowledge from two major fields that shape the theoretical background, namely:

1. Technology Adoption and Innovation Theories. The conceptual framework of technological readiness, organizational capabilities, and external environmental pressures for the adoption of innovation draws on the Technology–Organization–Environment framework - TOE framework (Tornatzky & Fleischer, 1990). This model identifies the tripartite technological, organizational, and environmental analytical framework that informs the research question.
2. Sustainability and Governance Frameworks. Theories of sustainable innovation, green computing, and environmental governance-most recently by Boiral et al. (2018) and Schiederig et al. (2012), enrich the environmental and policy dimensions of the study. It places the research within the broader theoretical context of sustainability policy and environmental regulation by aligning with global and regional regulatory frameworks like the UN SDGs and the European Union's AI Act and Ecodesign Directives (European Commission 2024; United Nations 2015).

This integrated approach enables the conceptualization of Green AI adoption both as a technological and organizational process and as a policy-driven and legitimacy-oriented transformation within the European regulatory landscape.

In sum, the integrated TOE, IRT and Institutional frameworks provide a multidimensional view of the drivers and barriers influencing Green AI adoption by capturing both the rational, capability-based determinants and legitimacy-oriented pressures that inform organizational choice. This forms a sound theoretical basis for

the empirical phase of this study, underpinning the development of Green AI Adoption Framework, as well as the formulation of policy recommendations that foster sustainable and ethical AI integration.

Rising concerns about the environmental implications of AI systems have driven researchers and practitioners to investigate methods that will make sure that AI systems remain highly efficient and sustainable (Verdecchia et al., 2023). This approach has resulted in Green AI, the approach that believes it is important to look at the costs involved regarding energy consumption, processing, and carbon emissions related to a model or systems (Tabbakh, A., 2024). Green AI adopts methods, tools, and best practices that address improvements regarding efficiency, transparency, and sustainability (Bolón-Canedo, V., 2024). As organizations embark on a journey that incorporates greater use of AI systems, it is important that it understands what influences Green AI adoption.

The TOE framework of Tornatzky and Fleischer (1990) conceptualizes the adoption of innovation at organizations as a function of interlinked technological, organizational, and environmental contexts. Thus, in the technological context, characteristics such as relative advantage, compatibility with existing infrastructure, and perceived complexity influence organizations' perceptions of the feasibility and usefulness of Green AI solutions. In this regard, the internal organizational context reflects conditions, an expression of managerial support, available resources, technical competencies, and organizational culture-affecting the organization's readiness for change. The environmental context refers to competitive dynamics, customer expectations, and regulatory pressures that encourage organizations to develop sustainable and responsible innovations. For these reasons, the TOE framework offers a comprehensive structure for identifying internal and external drivers at the organizational level for the adoption of Green AI. (Tornatzky & Fleischer, 1990).

However, organizational adoption of environmentally oriented technologies is not solely driven by internal evaluations but also by external social, regulatory, and professional pressures. To address these influences, the framework embeds Institutional Theory (DiMaggio & Powell, 1983), explaining why organizations conform to institutional expectations and, in turn, become increasingly similar over time through coercive, normative, and mimetic pressures. Coercive pressures arise from

regulations, government policies, industry standards, and ESG reporting requirements that force organizations to pursue sustainable technological practices. Normative pressures emanate from professional norms, best practices, and expectations provided by industry associations on responsible AI use. Mimetic pressures occur when organizations mimic competitors or industry leaders that successfully implemented Green AI, especially under uncertainty or rapid technological evolution. These institutional forces extend the TOE framework by focusing on the socio-political environment that influences perceptions of usefulness, legitimacy, and necessity in the adoption of Green AI. (DiMaggio & Powell, 1983).

Integrating TOE, IRT and Institutional Theory allows for a multidimensional understanding of Green AI adoption and governance. The conceptual framework for Sustainable Green AI Governance comprises two interconnected loops: 1) The 'Green-by-Design AI Loop' focuses on the internal efficiency of AI systems—reducing energy intensity, promoting low-carbon model architectures, and embedding sustainability metrics into AI development (Verdecchia et al., 2023; Clemm et al., 2024), and 2) The 'Green-via-AI Value Loop' captures AI's contribution to broader ESG outcomes, including environmental performance, circular economy strategies, and responsible innovation (Weng et al., 2025; Yu et al., 2025).

Institutional Theory integrates these loops by explaining how external legitimacy pressures (coercive, normative, mimetic) drive organizations to institutionalize Green AI policies and disclose sustainability metrics. The framework thus positions Green AI adoption as both a technological transition and an institutional response to sustainability imperatives (Scott, W. R., 2004; Latif, B. 2020).

2.3 Research framework and question

Against this contextual and theoretical setting, the present study aims to identify and analyze the main factors that influence the adoption of Green AI at technological, organizational, and environmental levels in Greece and the European Union. Based on the TOE framework of Tornatzky & Fleischer, 1990, the TAM (Davis, 1989), the IRT (Ram & Sheth, 1989) and Institutional Theory by DiMaggio & Powell, 1983, this research tries to develop an integrated approach concerning the extent to

which the internal capacities, along with the external pressures and regulatory environments, contribute jointly to the transition towards sustainable AI practices. Accordingly, the central research question guiding this thesis is: What are the factor-drivers, barriers, and regulatory frameworks that shape the adoption of Green AI across organizational, technological, and environmental dimensions, and how can these insights guide the development of responsible practices for the adoption of Green AI policy and governance within Greece and the European Union? To address this overarching question, the study is structured around the following sub-questions:

1. Technology Dimension – Drivers & Barriers: What kind of technological aspects like compute capabilities or innovation abilities can act as a catalyst or a barrier for the adoption of Green AI methodologies in the European context?
2. Organizational Dimension - Strategic and Cultural Factors: How do organizational capabilities, leadership support, financial budgets, or internal sustainability cultures affect the embedment of Green AI philosophy in operations?
3. Environmental and Institutional Dimension – Policy and Governance Contexts: How do European Union regulation systems, state policy tools, and institutional forces affect the speed and orientation of the adoption of Green AI solutions?
4. Integration and Policy Implications: How do the findings of these dimensions contribute to policy framework integration and the construction of appropriate governance structures for the responsible use of AI in the context of EU sustainability goals?

All the above questions are addressed in this research, seeking to establish an overarching and empirically supported framework which will, in turn, bridge the gap between the goals of sustainability and innovation policy regarding Green artificial intelligence adoption practices.

2.4 Analysis of SLR

Green artificial intelligence appears in the literature as approaches that prioritize energy and carbon efficiency across the entire AI lifecycle. Studies use terms such as “sustainable AI” and “eco-friendly AI” to describe, in addition to energy and carbon reduction, broader concerns of transparency, fairness, and alignment with global sustainability goals (Verdecchia et al., 2023). Metrics focus on energy consumption

(e.g., Joules, kilowatt-hours, megawatt-hours) and carbon emissions (e.g., kilograms and tons CO₂), sometimes extending to hardware efficiency and material waste. For example, 28 studies assess energy and carbon metrics, with evaluations covering training (18 studies), inference, deployment, manufacturing, and disposal.

The reviewed papers describe conceptual and practical frameworks that integrate technological, organizational, and environmental (TOE) factors. Some propose evolutionary sampling or multi-layered optimization, while others combine the Technology-Organization-Environment model with established methods such as the Technology Acceptance Model. Several studies invoke Innovation Resistance Theory to explain barriers that include technical complexity, high costs, limited expertise, and regulatory gaps (Haq et al., 2025; Verdecchia et al., 2023). Notably, 23 studies support lifecycle-based models that address multiple stages, from design and development to retirement, while 12 focus on stage-specific approaches. In the realm of policy, papers frequently reference the European Union Artificial Intelligence Act yet note its lack of clear sustainability indicators and lifecycle assessment criteria (Verdecchia et al., 2023; Le Goff, 2026).

The adoption of Green AI depends on a combination of organizational, technological, and environmental factors. Leadership commitment, resource allocation, and cross-functional collaboration are consistently cited as organizational factors, while challenges such as resource constraints, resistance to change, and lack of clear incentives hinder its implementation (Haq et al., 2025). Technological progress depends on algorithmic innovations, scalable hardware, and energy-efficient designs; yet studies also report concerns over high energy consumption, infrastructure gaps, and technical complexity. Environmental drivers are predominantly linked to regulatory pressure and the pursuit of sustainability goals, including alignment with United Nations Sustainable Development Goals (Verdecchia et al., 2023; Haq et al., 2025).

European Union policy instruments such as the Artificial Intelligence Act, eco-design directives, and mandatory energy reporting are recognized for promoting Green AI deployment (Dash, 2025; Clemm et al., 2024; Mu et al., 2025). At the same time, gaps in standardization, enforcement, and cross-jurisdictional harmonization persist (Alzoubi & Mishra, 2024; Verdecchia et al., 2023). The reviewed studies indicate that

robust leadership, measurable efficiency standards, and coordinated public, private partnerships can guide the responsible adoption of Green AI technology under the European Union's governance frameworks.

Though scholarly interest in Green AI is quickly expanding, literature as a topic is currently fragmented in nature, has limited empirical data and located in several geographic settings, thus, impeding on developing a single cohesive body of knowledge around Sustainable AI adoption. There are three primary areas where significant gaps exist. First, there is a lack of empirical validation. Most of the studies conducted thus far provide only exploratory/conceptual insights and lack large sample empirical studies. As noted in the article by Raman et al. (2024), most current research lacks longitudinal and industry level datasets. Likewise, studies by Haq & Suki (2025) and Azhar et al. (2025), conducted only among specific developing economies, are limited in their generalizability to other countries and their unique institutional and regulatory environments. Second, the literature has been concentrated in Asia and other emerging markets (i.e., Pakistan, China, and India). Examples include the work of Haq & Suki (2025) and Azhar et al. (2025), and Raman et al. (2024). Therefore, relatively little is known regarding the impact of European regulations, institutional maturity and policy incentives, on Green AI/bio-Materials adoption, essentially limiting the applicability of current findings on a global scale. Furthermore, current research is hindered by insufficient evidence from multiple sectors, since many researchers have evaluated only those sectors where they have a specific professional interest (manufacturing and service or hospitality). Conversely, other sectors that are both fundamentally important (e.g., public sector administration, health services, financial services, agricultural) and therefore of interest to researchers in general remain relatively under-represented, or unexamined, in the current literature. For example, Weng's (2025) research focuses on the manufacturing sector, whereas Azhar et al.'s (2025) research focuses on the service sector. Without multi-sectoral examination, both theoretical and practical applications become limited because there are fewer ways to validate existing models and/or build new and better models using existing building blocks to generate new models. Another key feature of this body of literature is its theoretical fragments. Current literature has favored using individual models/frameworks (TOE framework by Haq & Suki (2025), TAM model by

Azhar et al. (2025), and ESG framework by Weng (2025)). Again, little effort has been devoted to integrating the technological, organizational, and institutional perspectives into one holistic framework, and the absence of such enables a loss of the potential explanatory value of this research, as well as prevents the development of holistic models which could represent the multi-level mechanisms that regulate sustainable AI adoption. Fifth, human and organizational dynamics are not adequately discussed. Literature is dominated by technological and performance-related indicators, while leadership, organizational culture, capacity for learning, and green human resource management are understudied. Verdecchia et al. (2023) identify this socio-technical gap and appeal for the need for clear consideration of human agency in transitions toward sustainable AI.

Finally, with regards to knowledge, there remain some gaps regarding measurement and governance. A standard of measurement with regards to green AI and its effects upon the planet has still not been developed, and relatively few people have examined what needs to be done to create green AI, particularly within the realm of policy and regulation (Verdecchia et al., 2023; Raman et al., 2024). All these issues and others basically constitute a demand for a need to create research based upon inter-regional and policy-focused models, particularly within the context of EU changes to policy and regulation.

Overall, these deficiencies suggest that while there is growing work on Green AI, there is also much disunity in terms of the methodologies used, empirical development, and geographical/industry imbalances. Hence, there is an urgent need for research that is more empirically oriented, cross-industry, cross-geographic in nature, incorporating technological, organizational/institutional, human factors, as well as policy formulation into unitary forms of analysis. This will also become necessary for industries to evolve into more ecologically conscious digital ecosystems for policymakers to take informed actions. The development of standardized measures of sustainability is to be seen as necessary.

2.5 Synthesized Research Gap

Although research about Green AI and its role in promoting, sustainability has expanded significantly over the last few years, the scholarly knowledge remains fragmented and theoretically narrow. Most of the current literature concentrates on conceptual or exploratory analyses with limited empirical validation; hence, the literature still lacks robust evidence regarding the real-world implications and effects of actual Green AI implementation. For example, Raman et al. (2024) undertook a bibliometric and integrative review that identified the conceptual maturity of the area but stressed the requirement for validation at an empirical and industry level. Correspondingly, Haq and Suki (2025) and Azhar et al. (2025) explored the adoption of AI at a specific national level—that is, Pakistan and China—relating these to sustainability performance using structural models. However, their samples, which are geographically bound, reduce the generalization of findings across different cultural and institutional settings. Finally, prior studies have been dominantly sector-specific, with overriding concern for the manufacturing and hospitality sectors (Weng, 2025; Azhar et al., 2025), leaving other crucial sectors like agriculture, healthcare, and public administration relatively unexplored.

In terms of conceptual foundations, a significant number of studies rely primarily on isolated analytical examples — such as the Technology-Organization-Environment (TOE) framework, the Technology Acceptance Model (TAM), or the Environment, Society, and Governance (ESG) perspectives (ESG) perspectives — without developing a comprehensive framework that captures the interdependencies and mutual influences between technological, organizational, and environmental dimensions. Recent review-based research highlights that studies on green artificial intelligence often adopt fragmented perspectives, limiting their ability to explain the dynamics of systemic adoption or interactions between levels (Raman et al., 2024; Verdecchia et al., 2023).

When examining research questions related to the adoption of green artificial intelligence, literature shows a disproportionate focus on issues of technological readiness and performance, while comparatively less attention is given to human and organizational factors. Elements such as green leadership, organizational culture, employee engagement, and management commitment have often not been adequately explored, despite evidence suggesting their decisive role in shaping the

outcomes of sustainability-oriented technology adoption. Several empirical studies show that neglecting these human-centered factors risks treating the adoption of Green AI as a neutral, technology-driven process rather than a socially embedded organizational transformation (Haq et al., 2025; Azhar et al., 2025).

Furthermore, a persistent methodological challenge in a significant portion of the Green AI literature concerns the absence of a common and standardized basis for measuring the "green outcome" of AI technologies. Studies repeatedly point to inconsistencies in how energy efficiency, environmental impact, and the contribution of AI systems to sustainability, as well as how AI can be used to support sustainability goals. The lack of harmonized metrics and evaluation frameworks significantly limits the comparability, reproducibility, and regulatory applicability of research findings (Verdecchia et al., 2023; Raman et al., 2024).

Finally, only a limited number of studies explicitly address general policies, governance, and ethical guidelines for the adoption of green artificial intelligence from a global or cross-border perspective. While sustainability and environmental goals are often recognized, comprehensive discussions on regulatory alignment, ethical governance, and long-term policy coherence remain insufficient, especially beyond regional or sectoral contexts (Weng, 2025; Azhar et al., 2025).

Institutionalization of Green AI from the governance point of view requires multi-level policy coordination that embeds sustainability concerns into the laws governing AI, their standards, and mechanisms of funding. Several governments have put forth incentive structures in the form of tax benefits, grants, or green certification for those AI systems that show measurable performance both environmentally and ethically (OECD, 2024; Nikiforova et al., 2025; Azhar et al., 2025; Weng, 2025). In this respect, future research for academia and policy researchers should focus on the development of robust metrics with which to assess AI's energy consumption and carbon emissions vis-à-vis creation of value in society (Barbierato & Gatti, 2024; Alzoubi et al., 2025; Wu et al., 2022). Empirical investigation is also warranted into the role of cross-sectoral collaboration in affecting the adoption of Green AI and into identifying contextual barriers that could hamper developments in this area (Mikalef et al., 2025; Gill & Nikiforova, 2025; Faizan ul Haq et al., 2025).

2.6 Policy - Regulatory Foundations of Green AI

Providing theoretical and policy foundations for Sustainable Artificial Intelligence (AI) within the European Union (EU), it synthesizes major legislative instruments, strategic initiatives, and conceptual frameworks relevant to AI development aligned with environmental sustainability and human-centric digital governance (European Commission, 2025). Figure 1 illustrates how EU sustainability governance and AI-specific regulations intersect to form the basis of Green AI.

EU Sustainability Frameworks
(Climate Law, Green Deal, Taxonomy)



AI Governance Frameworks
(AI Act, Trustworthy AI, Data Regulations)

Figure 1. Conceptual Position of Green AI in the EU Policy Ecosystem

The idea of Green AI in the EU is based on the integration of the digital and climate governance frameworks of the EU (Gailhofer et al., 2021) as shown in table 1. The binding target of the EU Climate Law for Climate Neutrality by 2050 includes provisions for emission reduction strategies for digital technologies and AI across every sector (European Union, 2021). The European Green Deal of 2019 also recognized that Digitalisation plays an enabling role in Sustainable Transformation but also acknowledged the significant volume of materials and energy consumed throughout the process of developing and testing AI models, hosting data and performing numerous learning iterations (European Commission, 2019. *The European Green Deal*, COM (2019) 640 final, Raman, R., Pattnaik, D., & Lak, H. H. (2024). This ideal is also included in the AI Act 2024, which has established Environmental Sustainability as part

of Human Centric Governance of AI in the EU. In addition to these AI-specific regulations, the Corporate Sustainability Reporting and Corporate Sustainability Due Diligence Directives have expanded the reporting and Environmental Responsibility obligations of Corporations who use AI extensively. The combined frameworks create an Integrated Framework that includes Environmental Sustainability as one of the main elements for the Governance of Artificial Intelligence. To illustrate this, Figure 1 shows that when evaluating deployments of AI Technology there must be consideration for the social/economic ramifications, ethical implications, as well as how do they fit into the EU's vision of achieving Sustainability Goals throughout their life cycle and meeting the obligations of climate change.

Table 1. Key EU Legislative Instruments Relevant to Green AI

Instrument	Relevance to Green AI	Year
European Climate Law	Legally binding climate neutrality target guiding digital energy use	2021
European Green Deal	Positions digitalisation as a driver of sustainability	2019
EU Taxonomy Regulation	Sets environmental criteria including DNSH (Do No Significant Harm)for economic activities	2020
AI Act	Integrates environmental sustainability into AI governance	2024
CSRD	Mandates sustainability reporting, including digital environmental impacts	2022
CSDDD	Introducing environmental due diligence for digital value chains	2024

Green AI refers to the creation, distribution, and regulation of any type of artificial intelligence in a manner that has a smaller impact on energy use, water usage, environmental impact, and resource use through the entire life span of the product (Verdecchia et al., 2023). In addition to the concerns regarding the impact on energy

use, the expansion of AI models over the last several years due to rapid growth in computationally intensive model, such as large language models, has increased governmental concerns about energy use, sustainability of data centers, externalities in the supply chain, and the environmental impact of the building infrastructure (Verdecchia et al., 2023; Raman et al., 2024). Within this context, the European Union has emerged as the most active global regulator shaping the environmental dimensions of AI, even though “Green AI” is not explicitly defined as a legal category in EU law (Verdecchia et al., 2023; Raman et al., 2024; Azhar et al., 2025). Instead, the regulatory foundations of Green AI arise through a constellation of legislative instruments that indirectly or directly shape sustainability outcomes in the digital ecosystem (European Union, 2024; Pouikli, 2025; Siegmann, 2022).

Green AI focuses on creating and deploying AI systems that reduce energy consumption, water use, and overall environmental impact. It targets increasing algorithmic efficiency and efficient training processes and supports sustainable infrastructure such as data centers and ICT equipment (Verdecchia et al., 2023; Raman et al., 2024). In the EU, Green AI is not subject to any single law but has a broad series of related policies, which include the AI Act, Energy Efficiency Directive (EED), Delegated Regulation on reporting by data centers, Ecodesign standards Lot 9 and ESPR, and corporate sustainability reporting frameworks like CSRD, ESRS, and the EU Taxonomy (Gailhofer, P., et al., 2021). Data governance laws, such as GDPR, the Data Act, and the Data Governance Act, also indirectly affect the sustainability of AI in terms of how data is accessed, processed, and managed.

At the core of the EU’s AI governance lies the Artificial Intelligence Act (Regulation (EU) 2024/1689), the first comprehensive horizontal AI law globally. While the AI Act primarily focuses on fundamental rights, safety, and systemic risk, it introduces for the first time transparency requirements related to the energy consumption of General-Purpose AI (GPAI), including foundation models. Providers must document actual or estimated energy use based on computers and provide technical documentation to regulators. The AI Act also introduces the notion of systemic-risk GPAI, recognising that very large AI models can impose significant resource burdens. However, the AI Act does not impose binding energy reduction targets nor performance thresholds and is therefore often characterized as a transparency-only environmental instrument

(European Union, 2024). The AI Act introduces disclosure and documentation obligations related to energy use for certain AI systems but does not establish binding quantitative environmental targets.

The second and more substantial regulatory component of the EU Green AI Framework is the EU Sustainability Framework for Data Centers. Data centers represent the physical infrastructure where all AI technologies are developed, deployed, and operated (European Commission, 2022). Through its Energy Efficiency Directive (EDD) (Directive (EU) 2023/1791), the EU establishes mandatory reporting requirements for any data center with a total electricity consumption from IT equipment exceeding 500 kilowatts (kW), as well as establishing several key performance indicators (KPIs) that must be provided for each data center. Establishing mandatory reporting for such large data centers through the Energy Efficiency Directive (EDD) will serve as a basis for creating a European Union-wide environmental database on the environmental footprint of large data centers. Through the requirements that the EDD imposes on large data centers, the European Union is providing its most significant effort to regulate and control the environmental impact of the physical infrastructure that supports all AI training and inference workloads.

Regulation for Servers and Storage Products (Reg. (EU) 2019/424) sets minimum energy performance standards for all Information and Communication Technology (ICT) Hardware that is involved with AI computation. In addition, the Ecodesign for Sustainable Products Regulation (ESPR) (Reg. (EU) 2024/1781) defines Digital Product Passports that will outline how durable and repairable an ICT device is, how recyclable it is and what energy efficiency rating it has. Finally, there are several different Corporate Sustainability Governance (CSG) Mechanisms in place to help reinforce the Green AI movement, including the Corporate Sustainability Reporting Directive (CSRD) (DIR. 2022/2464) and the European Sustainability Reporting Standards (ESRS), which require companies to disclose their emissions (Scopes 1-3), their energy consumption, their environmental impacts related to digital systems, and their plans related to climate transition. Similarly, the EU Taxonomy (Reg. 2020/852) defines when investments in data hosting or processing qualify as environmentally sustainable, based on stringent technical screening criteria. Moreover, Data governance frameworks influence Green AI too. The GDPR (Reg. 2016/679) promotes efficiency by

mandating data minimization and privacy-by-design, which can reduce unnecessary data processing and computational overhead. The Data Act (Reg. 2023/2854) and Data Governance Act (Reg. 2022/868) increase the availability of high-quality data for energy optimization, environmental monitoring, and climate modelling—enabling “green-by-data” AI applications. Although there has been progress, many gaps still need to be filled. The current regulations do not include AI models as they only focus on the performance of the infrastructure. This means there is no regulation in place for the energy efficiency or emission levels of AI models. As there are no legally binding limits on the amount of carbon emitted during each training run or inference call in the EU. According to the European Union (2024), Strubell et al., (2019), Lannelongue et al. (2021) and many others in the academic community have indicated that there is a lack of standardized methodologies for measuring carbon and energy footprints of AI systems in Europe. Future regulatory development is likely to move towards environmental performance standards, minimum efficiency requirements in high-compute models and lifecycle regulation of AI hardware (Verdecchia et al., 2023; Raman et al., 2024).

In sum, the regulatory foundations of Green AI in Europe can be understood as a hybrid framework emerging from AI-specific law, energy regulation, product sustainability frameworks, data governance, and corporate reporting legislation. While the EU provides the most comprehensive global architecture for sustainable AI, the absence of binding environmental performance obligations for AI models indicates that the field remains in an early regulatory phase (European Union, 2024-AI Act). As AI systems become more computationally intensive, sustainability will increasingly become a central regulatory concern rather than a peripheral one (Schwartz et al., 2020).

This chapter provides an in-depth review of the regulatory landscape for Green AI, discussing not only significant developments and existing gaps, but also emerging challenges that must be met.

2.7 Current situation in Greece

Greece is undergoing a period of accelerating digital transformation, accompanied by significant investments in artificial intelligence (AI), cloud infrastructure, and data-

driven innovation (Trade.gov, 2025; Greece AI Transformation Blueprint, OECD, 2025). However, the systematic integration of Green Artificial Intelligence (Green AI), that is that AI is both environmentally efficient and supportive of environmental goals—remains at an emerging stage (Verdecchia et al., 2023; Henderson et al., 2020; Tabbakh et al., 2024; Singh et al., 2024).

Greece is setting up a comprehensive national framework to govern the use of Artificial Intelligence (AI) in ways that are fair and equitable to all citizens. The document which was published by the Greek Ministry of Digital Governance (2024) and is titled “Plan for the Transformation of Greece through Artificial Intelligence”, states that developing a guiding framework for developing and implementing AI technologies is critical to the sustainable development of the country. However, in developing the guiding principles for AI and their governance within Greece, there are no provisions for the inclusion of the environment or the sustainability of AI as part of the national governance framework (Blueprint for Greece’s AI Transformation, 2024). Greece is working to align its regulatory environment with the EU Artificial Intelligence Act (European Commission, 2024) which establishes risk-based regulations for AI systems. The EU AI Act does not establish specific legislation for Green AI, however the provisions outlined in the EU AI Act relating to robustness, efficiency, and lifecycle risk management indirectly support efforts to reduce the negative environmental impact of developing and deploying AI technology (Veale & Zuiderveen Borgesius, 2021). Thus, Greece is well-positioned to incorporate environmental performance metrics into regulatory frameworks at the national level in the future.

Greece’s broader digital transformation strategy, as articulated in the Digital Transformation Bible 2020–2025 (Ministry of Digital Governance, 2020), and the country’s National Recovery and Resilience Plan (Greece 2.0) (Hellenic Republic, 2021), emphasizes the interconnection between digital innovation and green transition. Similarly, the National Energy and Climate Plan (NECP) provide a strategic pathway for achieving climate neutrality by 2050 (Ministry of Environment and Energy, 2019). Nevertheless, none of these frameworks include a dedicated operationalization of Green AI. Sustainability considerations mainly appear as general principles rather than binding requirements for AI-enabled systems or data infrastructures (Gunasekara et al., 2025; Maunier & Vandewalle, 2025; Le Goff, 2025).

Despite this policy gap, Greece has made important advances in national AI and computing infrastructure. Initiatives such as the Pharos Artificial Intelligence Factory, designated as one of the first EU-wide AI Factories under the Digital Europe Programme, and the national DAEDALUS managed by GRNET, expand the country's computational capacity (CORDIS, 2025; EuroHPC Joint Undertaking, 2024; GRNET S.A., 2025). However, these infrastructures do not yet incorporate mandatory environmental performance indicators, such as Power Usage Effectiveness (PUE), Water Usage Effectiveness (WUE), or minimum renewable energy thresholds, which are essential features of Green AI infrastructures.

Overall, Greece demonstrates strong political momentum in AI policy development. Yet the explicit integration of Green AI as a horizontal policy objective remains incomplete, representing a key opportunity for the national AI strategy moving forward.

Although Greece has not yet established standardized national indicators for Green AI, available evidence suggests that its systematic adoption may generate significant environmental, economic, and social benefits (European Commission, 2025: *Greece AI Strategy Report*).

Environmental Impact

Green AI techniques can address the energy consumption and carbon emissions created by both artificial intelligence and its usage across various industries. In the case of buildings and energy management, AI can enhance the efficiency of the smart grid, district heating and other large buildings through things such as optimizing operation, as well as optimizing energy consumption/demand forecasts, and this aligns with the objectives discussed in the NECP document (Ministry of Environment and Energy 2019).

Economic Impact

Green AI can help Greece become more competitive in export-oriented sectors such as agritech, logistics, and tourism through the development of Green AI capabilities and by reducing the costs associated with operating AI infrastructures (e.g., energy-driven data centre operation). Lotsis (2025) shows how AI tools can support agri-tourism integration and streamline cooperative logistics, enhancing environmental monitoring and resource efficiency. Sustainable AI infrastructures have been shown

by studies at the EU level to produce measurable productivity gains while also lowering the total overhead cost of electricity consumed by these infrastructures. (The European Commission, 2020; Bolón-Canedo et al. 2024).

Social and Public Sector Impact

By incorporating the Green AI concept into their existing strategies, Allies, including Greece, may enhance climate resiliency which is an important National Priority by providing improved response and reaction capabilities in areas such as predication of wildfire risk, flood modelling, disaster response and environmental monitoring of climate issues. Sustainability incorporated into the design and implementation of AI systems will help increase public confidence and acceptance of AI systems by the public and thus the successful implementation of AI into Greece's digital transformation agenda will be more sustainable. Although there is a growing world-wide interest in developing environmentally sustainable artificial intelligence (AI), Green AI has not yet been systematically integrated into National Strategy/Organizational Adoption Frameworks (OECD, 2018). Greek examples of how environmentally sustainable AI systems can be seen in some of the projects currently being developed around sustainability with existing AI technology. The AI4EF project established within the context of building optimization (Tzortzis et al., 2025) is one of those examples as well as AI for municipal energy management that is currently being developed by the municipality of Trikala (Chasiotis, A. et al., 2025). These two projects are excellent examples of the practical application of Green AI in Greece however neither project has been presented with an organized adoption framework for developing Green AI systems in Greece. Greece's National Policy papers e.g. "A Blueprint for Greece's AI Transformation" (Ministry of Digital Governance, 2024) explicitly states that AI will be transformative, but there is no mention of incorporating environmental performance indicators as part of developing and rolling out Green AI within Greece. Although the TOE framework is widely used to study AI adoption internationally (Higón et al., 2025) and has been applied in Greece for conventional AI adoption (Papathomas, et. al., 2025), no published work has extended TOE to the specific context of Green AI adoption in Greece. Thus, the literature reveals a clear gap: there is no integrated Green AI adoption framework designed for the Greek ecosystem.

Many researchers are studying ways to provide artificial intelligence (AI) systems with energy-efficient methods. These include techniques that compress models, i.e., reduce their size, quantization, which makes numbers smaller, using lighter-weight sparse networks and developing better ways to train AI models (Bolón-Canedo et al. 2024; Różycki 2025). In doing so, researchers believe it is possible to provide AI models with more computational efficiency and therefore a lower environmental impact. In addition, these energy-efficient techniques are being used to support many sustainability-related activities. Some positive examples of sustainability-related activities that benefit from machine learning include Supporting crop management through renewable energy forecasting; Supporting sustainable agricultural practices; and supporting sustainable environmental monitoring (Papadopoulos et al. 2022; European Commission 2022; European Commission Joint Research Centre 2023). Additionally, there are start-ups and other organizations located in Greece, like AGENSO, that are focused on the development of various digital technologies and AI-based services/products, focusing particularly on the achievement of environmental goals, thanks to the high skill levels possessed by its workforce, along with its involvement in European research projects, as demonstrated through the Elevate Greece initiative (AGENSO n.d.; Elevate Greece n.d.). However, challenges remain in terms of the scale of applications, the establishment of uniform standards for measuring the energy footprint, and the need for a coherent policy that integrates digital, energy, and environmental strategies. High levels of social skepticism about AI highlight the need for institutional support and reinforcement of the ethical dimension of technology.

Greece has been advancing green infrastructure and sustainable digital innovation through major national initiatives. The National Recovery and Resilience Plan “Greece 2.0” prioritizes renewable energy, energy-efficient buildings, and modern digital systems (Government of the Hellenic Republic, 2021). This is complemented by the National Digital Decade Roadmap, which aligns technological development with long-term environmental goals (European Commission, 2023). Pilot projects such as the Ai Stratis Green Island highlight Greece’s commitment to scalable renewable solutions (CRES & HEDNO, n.d.).

At the same time, Greece is supporting the expansion of green AI applications. Horizon Europe projects, including those led by the Technical University of Crete, apply AI and machine learning to improve energy forecasting and optimize building performance (Technical University of Crete, 2025). The LEIF project further demonstrates how AI can enhance sustainable finance and support environmentally responsible investments (NTUA-EPU, 2024).

Policy frameworks reinforce these efforts. The European Commission's AI Watch report notes Greece's plan to implement pilot AI applications across policy sectors (AI Watch/European Commission, 2020). The national "Blueprint for Greece's AI Transformation" outlines long-term priorities to strengthen research, innovation, and flagship AI programs (High-Level Advisory Committee on Artificial Intelligence, 2024). Strategic foresight studies also emphasize the importance of AI for sustainability and energy efficiency (EKKE & NCSR "Demokritos," 2024).

Finally, Greece is strengthening its international profile in AI through global partnerships such as the OpenAI for Greece initiative, which introduces pilot AI deployments in education and supports AI-focused entrepreneurship (OpenAI & Government of Greece, 2025). International assessments from the OECD recognize Greece's growing readiness and strategic commitment to AI development (OECD, 2025).

3. Methodology

Building on the conceptual foundations and policy implications outlined in the previous chapter, this section presents the methodological approach used to investigate the adoption practices of Green AI across all sectors, public and private.

3.1 Introduction

This chapter outlines the **research methodology** employed to achieve the objectives of the study, which seeks to examine current Green AI adoption practices across public and private sectors. Guided by a mixed-methods design, the study integrates

systematic literature review, policy analysis, and empirical investigation to capture both the structural and contextual dynamics shaping Green AI adoption.

The methodological approach is structured around three interrelated phases. The two first phases aimed to establish the **conceptual and policy foundation** for Green AI adoption by conducting a **Systematic Literature Review (SLR)** on Green AI adoption and analyzing **European Union (EU)** legislative and strategic frameworks.

1. **Analysis of the Systematic Literature Review.** The above analysis is complemented by a Systematic Literature Review (SLR) focusing on Green AI adoption trends, barriers, and best practices across various sectors. Together, these steps establish the conceptual and policy foundation of research, identifying theoretical gaps and emerging directions for Green AI adoption practices and sustainable AI governance.
2. **Analysis of EU Policy and Regulatory Frameworks** — The second phase involves an in-depth examination of **European Union** policy and regulatory acts related to AI, sustainability, and digital transformation and other national, European and global regulation frameworks, including the *EU Artificial Intelligence Act (2024)*, *European Green Deal* frameworks and more.
3. **Examination of Current Practices through Semi-Structured Interviews** — The third phase adopts a qualitative empirical approach to explore current Green AI adoption practices in Greece. Semi-structured interviews are conducted with experts, policymakers, and practitioners involved in AI development, governance, and sustainability initiatives. The interview guide has been developed using the Technology-Organization-Environment (TOE) framework, Innovation Resistance Theory (IRT) and Institutional Theory (IT) which provides the basis for identifying both internal and external factors in relation to the adoption of Green AI. The rich contextual information from the interviews will reveal how organizations operationalize Green AI principles and will identify what is driving these behaviors, what constraints exist, and provide cross-sectoral variation in these behaviors.

Utilizing a mixed-methods approach to obtain data for this study will allow for an overall multi-layered analysis which will combine the systematic rigor associated with the policy and literature synthesis process with the contextual richness associated

with the qualitative inquiry of SMEs. The quantitative insights gained through the systematic literature review, as a result of the review of 22 peer-reviewed articles will, along with the qualitative data obtained through semi-structured interviews of experts when analyzed together, will provide a fuller understanding of how the interactions between policy frameworks and organizational practice influence the adoption of Green AI (Bryman, 2006). A mixed-methods design that has used methodological triangulation has been employed by using both qualitative data and quantitative data to strengthen the credibility, relevance, and applicability of the findings (Creswell & Plano Clark, 2018). Utilizing multiple research methods has increased the validity and reliability of the findings by cross-verifying evidence through data obtained from different sources (Creswell & Plano Clark, 2018).

Overall, this methodological structure aligns with the study's conceptual foundations, particularly the Technology–Organization–Environment (TOE), Innovation Resistance Theory (IRT) and Institutional Theory (IT) frameworks, which explain how technological capabilities, organizational readiness, and external pressures shape innovation adoption.

3.2 Research Philosophy

This study uses the philosophy of pragmatism and accepts the limitations of only relying on the traditional scientific epistemologies for producing knowledge of complex social & technological phenomena, like Green AI. Pragmatism emphasizes the research problem, in this case, discovering how to adopt Green AI, and therefore lends itself to providing many ways (or methods) to find the best way to implement Green AI (Creswell and Plano Clark, 2018). The diverse use of the pragmatic paradigm supports the use of multiple methodologies. In this case, the method used to explore questions of research would include both qualitative and quantitative data, from multiple complementary perspectives. This is an ideal fit for Green AI's multiple disciplines: Technology, Ethics, Environmental Policy, and Organizational Management. The goal of this project is to produce results that will influence decision-making on how to create and implement sustainable AI strategies using an action-oriented approach, which correlates to a pragmatic design. The project will provide

practical insights and actionable recommendations for creating and supporting ethical and environmentally responsible AI innovation is by developing applicable theories within the theoretical discourse around Green AI and sustainable AI governance. The sequence and integration of the research methodologies used in this study are illustrated in Figure 2.

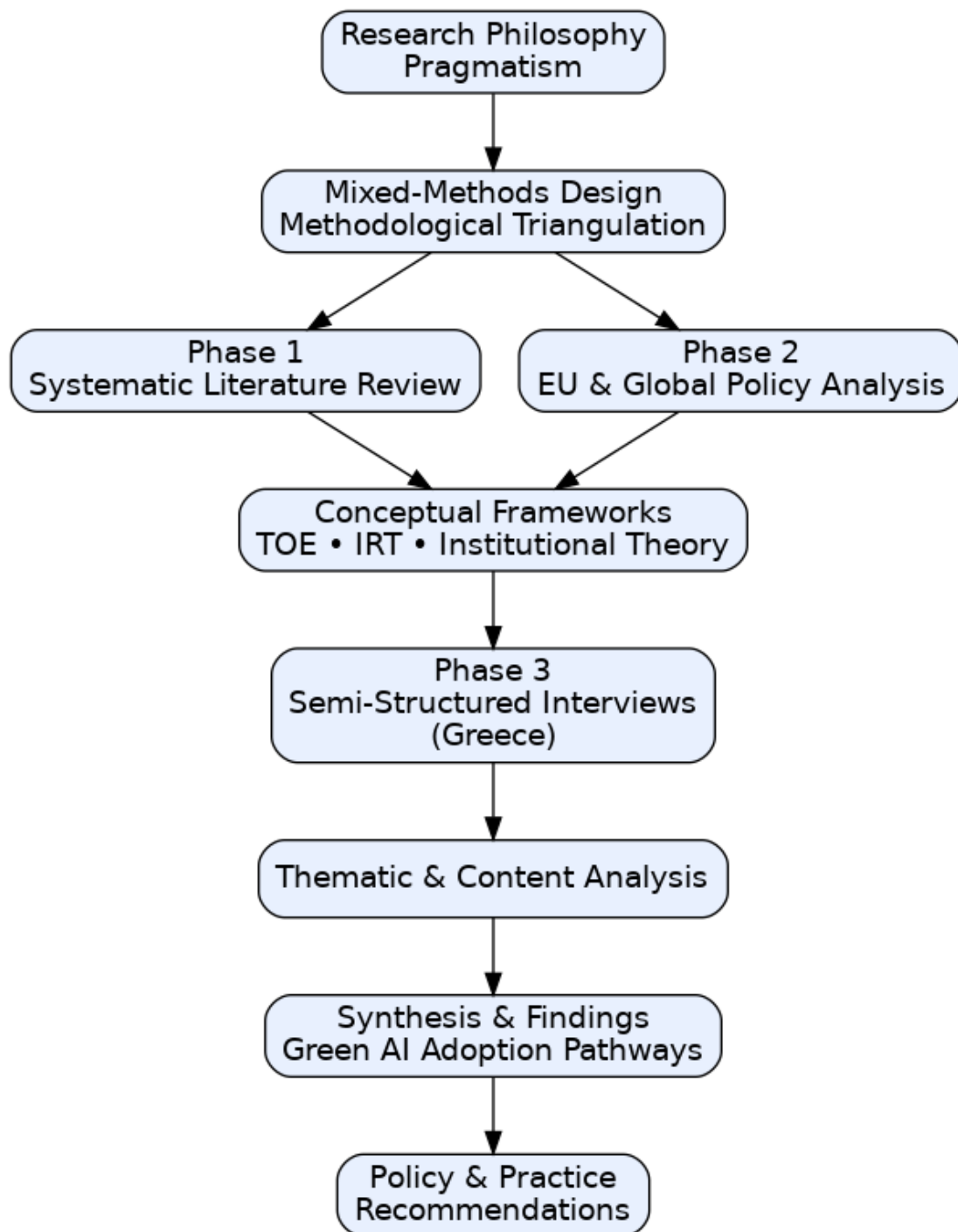


Figure 2: Research Methodology Framework

3.3 Data Collection Methods

The data collection process was designed to align with the main objectives of the study and the mixed-methods research strategy outlined earlier. Each phase contributes complementary insights into the adoption of Green AI practices across the public and private sectors. The methods employed include: (1) a systematic literature review on Green AI adoption practices and documentary and literature-based analysis of EU policy and regulatory acts (2) semi-structured interviews exploring current RGAI adoption practices, and

3.3.1 Systematic Literature Review

A **Systematic Literature Review** was conducted to synthesize existing academic and policy-oriented studies on Green AI adoption, focusing on factors-drivers, barriers and regulatory frameworks that shape the adoption of Green Artificial Intelligence (Green AI) across organizational, technological, and environmental dimensions, in accordance with the guidelines proposed by Kitchenham et al. (2009). The goal of this research can be directly translated into a research question (RQ): “What factors-drivers, barriers, and regulatory frameworks shape the adoption of Green Artificial Intelligence (Green AI) across organizational, technological and environmental dimensions, and how can these insights guide the development of adoption practices of Green AI policy and governance within the European Union?”. By answering the research question, we aim at gaining a systematic overview of the Green AI adoption characteristics, parameters and practices, starting from a detailed analysis of the last two years regarding drivers, barriers of Green AI Adoption, the regulatory frameworks and policy implications, policy gaps and opportunities. The review was drawn from digital libraries indexed in Scopus, Web of Science (WoS) supplemented by Google Scholar, to ensure a comprehensive and peer-reviewed selection of academic sources. The search strategy combined the search terms and keywords such as “Green AI”, “sustainable AI,” “Green AI adoption practices,” “sustainable AI governance,” “green AI governance” “Low-carbon AI”, “Environmentally responsible AI”, “Carbon footprint of AI”, and “Energy-efficient machine learning».

The first search was based on keywords “Green AI” and “sustainable AI governance”. The second research string focused on Green AI and its adoption practices. Both ways of search were applied to the title, abstract, and keywords ensuring that these were the main research topics of the selected papers and then to the entire text, allowing for the discovery of more relevant data related to the research question. Only English-language sources, including journal articles, conference papers, book chapters, short surveys, and letters, published between 2023 and 2025, were included in the review to capture the rapid evolution of the field. Research on the topic of green artificial intelligence was minimal from 2000 to 2023. I searched for articles from 2023 to determine how thoroughly the issue had been researched up to that point. I decided to choose one paper from 2023 because it was a systematic literature review and was quite interesting as an introduction to the subject of all the research that preceded it. Most articles related to the above keywords were selected between 2024 and 2025, with the most in 2025, given that recent research and engagement with the topic of Green AI have begun to get more intensive in 2025.

The database search yielded 326 records from Scopus, Web of Science and Google Scholar (as of September 2025). After deduplication, two independent reviewers conducted an initial screening of the titles and abstracts based on predefined inclusion and exclusion criteria, emphasizing the relevance of each study to Green artificial intelligence (AI) adoption parameters. Any inconsistencies in screening decisions were addressed through discussion or adjudication by a third reviewer, leading to the exclusion of 191 studies that fell outside the defined scope.

Subsequently, the full texts of the remaining 135 publications were retrieved for an in-depth assessment of their conceptual and empirical contributions to understanding the scope of green artificial intelligence, the factors that favor its adoption, the barriers to its adoption, the regulatory and policy frameworks that relate to factors operating in the three specific dimensions, namely the organizational, technological and environmental dimensions, as well as how the Innovation Resistance Theory (IRT) and institutional theory (IT) could influence the adoption of specific practices. TOE, IRT and IT are strong for adoption, and fully capture (1) resistance factors, (2) human–technology interactions, (3) long-term capability building (digital resilience), (4) ethical trade-offs, (5) lifecycle sustainability of AI systems. A socio-organizational change, not

just an innovation adoption, thus, Science and Technology studies (STS) lenses are very relevant. Moreover, IRT examines why organizations hesitate to adopt Green AI practices (e.g., cost, complexity, perceived risk), explaining (1) functional barriers (complexity, performance risk), (2) psychological barriers (tradition, image), (3) economic barriers, which are every relevant when it comes to the very emerging field like Green AI can be seen. It thus can complement TOE nicely by adding a layer of adoption inhibitors – little additions as much overlap with TOE but much more interesting results. As in the previous stage, disagreements were resolved through consensus or third-party review, resulting in a final body of 35 studies selected for comprehensive thematic analysis. The systematic literature review followed the PRISMA guidelines, ensuring transparency and methodological rigor in the identification and selection of relevant studies (see Figure 3).

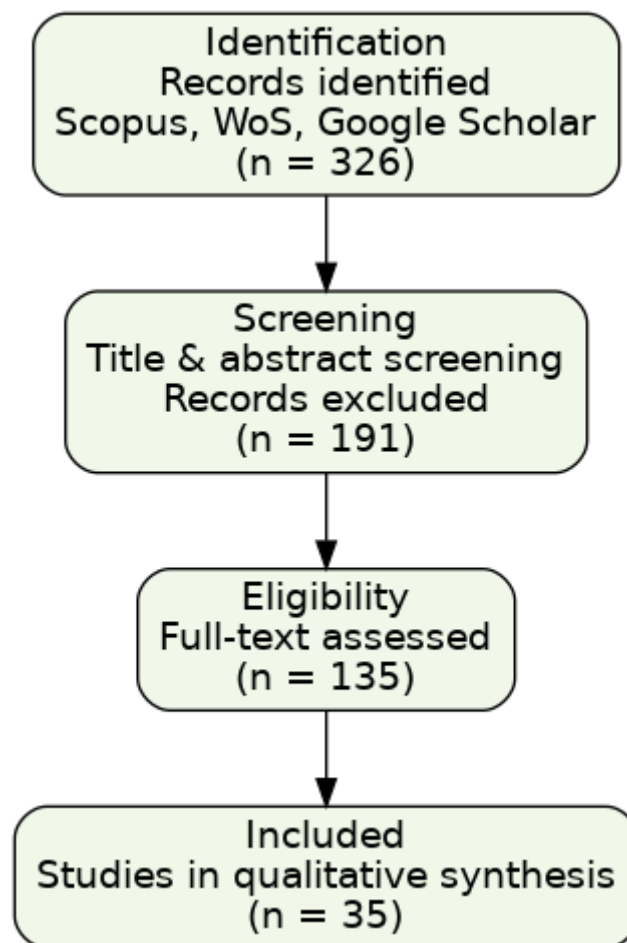


Figure 3: PRISMA flow diagram of the systematic literature review

The findings provided the theoretical grounding for the subsequent qualitative phase and guided the formulation of the interview protocol, ensuring conceptual consistency with the Technology–Organization–Environment (TOE) framework, the Innovation Resistance Theory (IRT) and Institutional Theory (IT).

3.3.2. EU Policy/Regulatory Acts

A qualitative **documentary analysis** was conducted to examine policy and regulatory documents that influence AI and sustainability governance. Key sources included national, EU and global regulations as well as:

- Law 5164/2024 (CSRD transposition) -Greece
- National Energy & Climate Plan (NECP 2024)- Greece
- National AI Strategy (2025)- Greece
- The EU Artificial Intelligence Act (2024),
- The European Green Deal (2020),
- The Digital Europe Programme (2021–2027),
- The Green Digital Transformation of Public Administration (European Commission, 2023),
- Relevant OECD and UNESCO frameworks on responsible and ethical AI.
- Energy Efficiency Directive (EED) (Directive (EU) 2023/1791)
- Commission Delegated Regulation (EU) 2024/1364 (DC reporting KPIs)
- Ecodesign Regulation (EU) 2019/424 (Lot 9: servers & storage)
- Ecodesign for Sustainable Products Regulation (ESPR) (EU) 2024/1781
- Corporate Sustainability Reporting Directive (CSRD) & ESRS
- EU Taxonomy (Reg. 2020/852) – Activity 8.1 (Data processing, hosting)
- EU Green Public Procurement (GPP) – DCs, server rooms & cloud (2020)
- Renewable Energy Directive (RED III) (EU) 2023/2413
- GDPR – General Data Protection Regulation (Regulation (EU) 2016/679)
- Data Act (Regulation (EU) 2023/2854)
- Germany – Energy Efficiency Act (EnEfG, 2023) – Global
- Singapore – Green Data Centre Roadmap (2024) – Global
- Netherlands – Local moratoria & zoning for hyperscale DCs – Global

- France – Energy Code amendments (heat-recovery obligation) – Global
- China – Green/Low-carbon Data-Centre Policy (various)- Global
- India – National Data Centre Policy (2020+) – Global
- USA – ENERGY STAR (servers, storage, DC equipment) – Global
- ISO/IEC 30134-2 (PUE) & 30134-9 (WUE) – Global
- ITU-T L.1300 – Best practices for green DCs- Global
- OECD AI Principles – Global
- Climate-Neutral Data Centre Pact (CNDP)- Global
- Green Software Foundation – Software Carbon Intensity (SCI)- Global

This research adopts a qualitative regulatory analysis approach to examine how existing European and regional legal instruments address environmental sustainability within the context of Artificial Intelligence (AI). The analysis focuses on identifying the extent to which current legislation supports the principles of 'Green AI', that is, the development and deployment of AI systems that are energy-efficient, resource-conscious, and environmentally responsible.

The study reviewed key EU legislative texts, including the Artificial Intelligence Act (AI Act), the Corporate Sustainability Reporting Directive (CSRD), the Corporate Sustainability Due Diligence Directive (CSDDD), the Energy Efficiency Directive (EED), and the Ecodesign for Sustainable Products Regulation (ESPR), the Data Act, GDPR and some more. The documents chosen for this study contained either a direct or indirect relation and relevance to Sustainable Development Goals, Transparency, and Digital Governance, therefore, each document was reviewed based on the following topics and criteria: Governance of Artificial Intelligence, Environmental performance of artificial intelligence, reporting on energy usage and lifecycle management of artificial intelligence systems. After that, thematic content analysis was performed on each document to identify policy objectives, regulatory mechanisms, and cross-sectoral connections related to 'Green' AI. This analysis provided an overview of the strengths, such as mandatory sustainability reporting, transparency of lifecycle, and obligations for energy efficiency and weaknesses such as, the fragmented governance of AI across sectors, lack of harmonization of instruments, limited coverage of software, and inadequate enforcement mechanisms.

3.3.3 Phase 3: Semi-Structured Interviews on Current Practices

The next phase employed semi-structured interviews to explore whether and how organizations, public and private, in Greece have incorporated green AI adoption practices into their systems design. This phase aimed to capture the lived experiences, institutional challenges, and strategic approaches of AI practitioners, policymakers, and sustainability experts.

3.3.3.1. Sampling and Participant Selection

A purposive sampling strategy was used to collect information from various stakeholders, including: (1) Public administration (government offices, digital agencies, ministries, regulators), (2) Private business (technology companies and AI startups), non-governmental organizations, and (3) Academic and research institutions involved in AI governance and sustainability studies.

Participants were selected based on their direct involvement in AI design, regulation, or strategy, and their expertise in sustainability or digital transformation. Approximately **10-12 interviews** were conducted until **thematic saturation** was achieved (Guest et al., 2020).

3.3.3.2. Interview Protocol and Design

The interview protocol was created using three perspectives from three different theories: Technology-Organization-Environment (TOE), Innovation Resistance Theory (IRT), and Institutional Theory. Based on the literature identified in the area, the interview protocol was designed around three major areas to encompass most of the conceptual dimensions identified by the literature: (a) Technology/Organization readiness for Green AI, (b) Types of Resistance/Perceived Barriers relating to Green AI, and (c) the institutional and policy environment shaping Green AI implementation. By bringing together this collection of approaches, a greater understanding of how Green AI adoption was influenced by the social, technological, organizational, and institutional contexts. It includes open-ended questions to allow participants to elaborate on their experiences, challenges, and recommendations. The interview protocol can be found in the Appendix.

Each interview lasted approximately 30–45 minutes and was conducted online (due to the participants availability). All sessions were audio-recorded with participant consent and transcribed verbatim for analysis. Interview transcriptions were produced using a customized version of the open-source Whisper speech recognition system developed by OpenAI.

The data collected will be analyzed using thematic coding aligned with TOE, Innovation Resistance Theory and Institutional Theory constructs. The coding framework includes the following categories: Technology (readiness, performance, measurement), Organization (leadership, skills, culture), Environment (regulation, market, infrastructure), Institutional pressures (coercive, normative, mimetic), and Outcomes (governance, sustainability, policy alignment). The coding process was guided by theoretically informed analytical dimensions, while the specific codes emerged inductively from the interview data.

Qualitative coding, based on the principles of thematic analysis, was used for the analysis of semi-structured interview data. First, a first-cycle coding process began, where line-by-line analysis of the data transcripts took place, accompanied by descriptive and conceptual coding. Then, with the coding of the second round, the initial codes were organized into larger categories and axes of themes, where the recurring patterns and meanings began to take shape. In such a way, the interpretation of the views and experiences of the participants became systematic, in-depth, and theoretically coherent and analytically valid (Saldaña, J., 2025). A hybrid coding approach is used for qualitative analysis by employing a mix of both deductive and inductive coding techniques. The broad themes used for the analysis were developed using a combination of literature and research framework (the three dimensions of Green AI Adoption are Organizational, Technological, and Environmental) and then used to structure the analyses of each interview. Based on the themes, a variety of codes were developed inductively through repeated iterations of analysis of all participants' interviews to identify patterns, barriers, and drivers in the data from the viewpoint of the participants. This approach allowed for both an empirical foundation and an openness to the data, reducing the impact of confirmation bias while maintaining analytical consistency.

3.3.4 Ethical Considerations

All research activities adhered to ethical research standards and the General Data Protection Regulation (GDPR) (EU 2016/679). Participants received detailed informed consent forms outlining the study's aims, confidentiality safeguards, and voluntary participation rights. Data was anonymized and stored securely.

3.4 Summary of the Methodology

This chapter presents the methodological framework designed to achieve the objectives of the study on Green AI adoption across the public and private sectors. Guided by a pragmatic philosophy and a mixed-methods research design, the study integrates policy and literature analysis and empirical inquiry, to ensure both analytical depth and practical relevance.

The first phase involved a Systematic Literature Review (SLR) and an analysis of EU policy and regulatory acts, thereby establishing the conceptual and policy foundations, identifying existing challenges, barriers, best practices, and theoretical gaps. The second phase employed semi-structured interviews in Greece to explore current adoption practices, drawing on the Technology–Organization–Environment (TOE) framework, Innovation Resistance Theory (IRT) and Institutional Theory (IT), regarding Environmental, Social, and Governance (ESG) principles to uncover the technological, organizational, and institutional dynamics influencing adoption.

Throughout the process, rigorous analytical procedures, including content and thematic analysis and triangulation, were applied to enhance the validity, reliability, and credibility of the results (Braun & Clarke, 2006; Creswell & Poth, 2018). Ethical compliance with GDPR and institutional research standards was maintained at every stage, ensuring data integrity and participant protection.

Overall, this methodology provides a systematic, transparent, and multi-dimensional approach for investigating the intersection of ethics, sustainability, and technological innovation in Green AI adoption. The following chapter presents the empirical findings and analytical insights derived from the data, demonstrating how the study's theoretical foundations and methodological strategies converge to inform the development of a Green AI adoption pathway across sectors.

4. Analysis and synthesis of the Results

This chapter focuses on the analysis and interpretation of the study results, synthesizing the theoretical and empirical findings that emerged from the systematic review of the literature, the analysis of the European regulatory framework, and qualitative empirical research (Creswell & Plano Clark, 2018; Patton, 2015). Unlike the previous chapters, which presented the theoretical and regulatory background, here the emphasis shifts from description to comparative interpretation, in line with the logic of analytical synthesis (Miles et al., 2014), with the aim of highlighting the factors that shape the adoption of Green Artificial Intelligence (Green AI) in practice. This chapter does not attempt to repeat or describe the findings, but rather to critically synthesize them in conjunction with the empirical data obtained from the qualitative research. The analysis is based on the logic of the Technology–Organization–Environment (TOE) and Innovation Resistance Theory (IRT), and Institutional Theory, to highlight the interactions between technological, organizational, and institutional factors that shape the adoption of Green Artificial Intelligence (Tornatzky & Fleischer, 1990; Ram & Sheth, 1989; DiMaggio & Powell, 1983). The conclusions of the chapter form the basis for the formulation and documentation of the proposed Green AI adoption framework and the corresponding policy recommendations.

The data analysis and presentation chapter outlines the research process findings. This chapter consisted of four phases. The first concerns the analyzed findings of the SLR, the second provides the analysis of the regulatory framework regarding sustainability of Green AI, and the third phase consist of the presentation of the empirical findings based on the interviews with key stakeholders (i.e., researchers, academics, advisors to government agencies and private entities) in Greece regarding the current status of adoption practices of Green AI technologies, highlighting sector-specific practices, enablers, and barriers to Green AI adoption in Greece. The fourth phase consists of the comparison of findings from the analysis of the institutional framework with the findings of the SLR and then their correlation with the empirical results of the interviews to answer the research questions posed at the beginning of the study.

This chapter interprets the findings from analysis of the data from the above two components based on the theoretical framework developed for this study (i.e., the

Technology-Organization-Environment (TOE) model, the Innovation resistant Technology (IRT) and the Institutional Theory (IT), concerning the ESG (Environmental, Social and Governance) principles.

4.1 Analysis and findings of the Systematic Literature Review (SLR)

To answer our research question «What factors/drivers, barriers, and regulatory frameworks shape the adoption of Green AI across organizational, technological, and environmental dimensions, and how can these insights guide the development of responsible practices of adoption of green AI policy and governance within the European Union?», we looked over 135 initial articles. Another approach to finding answers to the above question was the analyzing of some sub-questions such as: (1) What definitions and conceptualizations of Green AI are used in literature? (2) What metrics and indicators are proposed for assessing AI's environmental impact? (3) What are the technological, organizational, and environmental (TOE) factors influencing Green AI adoption? (4) How does the Innovation Resistance Theory (IRT) explain barriers to sustainable AI adoption? (5) What gaps exist in current policies and frameworks regarding Green AI governance?».

From the above/initial articles reviewed, I selected those that met these criteria:

- **Green AI Adoption Focus:** Does the study focus on Green AI, Sustainable AI, or Environmentally Responsible AI by addressing environmental aspects of artificial intelligence systems (such as energy efficiency, carbon footprint, or sustainability considerations)? Does this study examine drivers, barriers, facilitators, or challenges related to the adoption of environmentally sustainable AI practices?
- **European Union Relevance:** Is this study conducted within EU member states, does it examine EU organizations, or does it analyze EU regulatory frameworks?
- **Evidence-Based Research:** Is this study primary research (qualitative, quantitative, mixed-methods), a case study, systematic review, meta-analysis, or policy analysis study that provides evidence-based insights?
- **Framework Dimension Alignment:** Does this study examine at least one of the following dimensions of Green AI adoption: organizational, technological, or environmental?

- **Beyond Technical Development:** Does this study examine adoption factors or organizational implementation contexts, rather than focusing solely on technical AI algorithm development?
- **Sustainability-Focused AI Ethics:** If this study addresses AI ethics, fairness, or bias, does it specifically address environmental sustainability or Green AI concepts?
- **Organizational or Policy Context:** Does this study focus on organizational contexts or policy implications, rather than exclusively on individual consumer behavior or personal AI use?
- **AI-Specific Environmental Technology:** Does this study specifically address AI or intelligent systems, rather than focusing on broader environmental technology adoption without AI focus?
- **Green AI Focus:** Does the study focus on Green AI, Sustainable AI, or Environmentally Responsible AI by addressing environmental aspects of artificial intelligence systems, such as energy efficiency, carbon footprint, or sustainability considerations?
- **Methodological or Empirical Contribution:** Does the study present at least one of the following: conceptual frameworks, theoretical models, practical implementation approaches, environmental impact assessment methodologies, or empirical research such as case studies, surveys, lifecycle assessments related to sustainable AI practices?
- **Publication Quality:** Is the study a peer-reviewed publication with substantial empirical or theoretical contribution, i.e., NOT merely an opinion piece, editorial, or brief commentary lacking rigorous methodology?
- **AI System Environmental Impact:** Does the study address the environmental impact of AI systems themselves, rather than focusing solely on using AI applications to solve environmental problems without considering the AI system's own sustainability?
- **Sustainability Context:** If the study involves technical optimization or algorithmic research, does it explicitly connect to environmental sustainability goals, rather than focusing purely on performance optimization without sustainability context?
- **Environmental Dimension:** Does the study include environmental sustainability components, rather than focusing exclusively on only social, ethical, or economic AI aspects without environmental considerations?

Based on the above criteria, following information was gathered from all the articles, as shown in table 2. For each column of the table, I manage to use the following extraction instructions.

Regarding the **Study Context** I used contextual information about the study including, Geographic location/region studied, sector or industry focus (e.g., healthcare, education, energy, general), organizational type(s) examined (e.g., universities, enterprises, public sector), study timeframe or data collection period and sample characteristics (size, demographics, organizational roles).

Regarding the **Green AI Scope** I tried to find and extract how the study defines or conceptualizes Green AI, including, explicit definition of Green AI provided, key aspects emphasized energy efficiency, carbon reduction, sustainable computing, etc., specific AI technologies or applications focused on environmental sustainability metrics or goals mentioned and relationship to broader sustainability frameworks (SDGs, circular economy, etc.).

Regarding **Adoption Drivers** I found all factors identified as promoting or facilitating Green AI adoption including, technological factors (readiness, infrastructure, capabilities), organizational factors (leadership support, resources, culture), environmental factors (regulatory pressure, sustainability goals), economic factors (cost savings, financial incentives), social factors (awareness, perceived benefits, stakeholder pressure) and individual factors (attitudes, intentions, skills).

Regarding **Adoption Barriers** all factors were identified as hindering or preventing Green AI adoption including, technological barriers (lack of infrastructure, technical complexity, interoperability), organizational barriers (resource constraints, resistance to change, lack of expertise), financial barriers (high costs, unclear ROI, funding limitations), regulatory barriers (unclear policies, compliance challenges), environmental barriers (energy constraints, sustainability conflicts) and knowledge barriers (awareness, understanding, skills gaps).

Regarding **Regulatory Frameworks** I found information about regulatory and policy frameworks including specific regulations, policies, or standards mentioned, regulatory bodies or organizations involved, compliance requirements or guidelines, policy gaps or needs identified, regulatory facilitators or barriers to adoption,

international frameworks referenced (EU policies, UN SDGs, etc.), recommendations for regulatory development and current regulatory landscape assessment

Furthermore, according to the **Dimensional Analysis** I found how factors operate across the three specified dimensions, such as, **Organizational dimensions**: internal factors, governance, decision-making processes, organizational capabilities, **Technological dimension**: technical infrastructure, AI algorithms, energy efficiency measures, computational aspects and **Environmental dimension**: sustainability impacts, carbon footprint, resource consumption, ecological effects and noted any interactions or trade-offs between dimensions.

According to the **Methodological Approach**, I noticed the research methodology including, Study design (quantitative, qualitative, mixed methods, systematic review, etc.), Data collection methods (surveys, interviews, experiments, literature review), Theoretical frameworks or models used (TOE, IRT, etc.), Analysis techniques employed, Sample or data sources and Validation methods if applicable.

Moreover, I tried to provide **Key Findings** about Green AI adoption including, main conclusions about adoption factors, quantitative results (percentages, effect sizes, performance metrics), significant relationships or correlations identified, effectiveness measures (energy savings, efficiency improvements), success factors or critical conditions for adoption, unexpected or counterintuitive findings and limitations or gaps in current adoption practices

Another searching outcome was to find out and provide the proposed **Recommendations** for specific policy and governance including, Recommendations for policymakers or regulatory bodies, Suggested policy instruments or mechanisms, Governance frameworks proposed, Best practices for responsible AI adoption, Implementation strategies or roadmaps, Stakeholder roles and responsibilities, Monitoring or evaluation approaches, Specific relevance to EU context if mentioned, Areas requiring further policy development.

And finally, extracting actionable insights and practical applications including, Implementation frameworks or guidelines provided, Tools, techniques, or technologies recommended, Scalability considerations and deployment strategies, Resource requirements and cost-benefit analyses, Stakeholder engagement approaches, Change management strategies, Success metrics and evaluation criteria,

Transferability to different contexts or sectors, Proposed practice of adoption of Green AI.

4.1.1 Results-Characteristics of Included Studies

Table 2: Characteristics of Included Studies

	Study	Study Focus	Research Question/Objective	Methodology	Geographic Context
1	Ranpara, 2025	Energy-efficient Green Artificial Intelligence for circular economies	Develop and test a multi-layered Green Artificial Intelligence framework for sustainable resource optimization	Quantitative, real-world datasets, optimization models	Urban (no mention found)
2	Alzou et al., 2025	Sustainable Artificial Intelligence in healthcare	Systematic review of Artificial Intelligence algorithms/ techniques for energy efficiency in healthcare	Systematic review, Preferred Reporting Items for Systematic Reviews and Meta-Analyses	Global (United States, United Kingdom focus)
3	Hasan et al., 2025	Carbon emission quantification in machine learning	Synthesize research on sustainable machine learning practices and carbon footprint tools	Systematic review, bibliometric	China (policy), global literature
4	Sumathi & Devilakshmi, "Green Artificial Intelligence"	Green Artificial Intelligence for sustainable innovation	Analyze Green Artificial Intelligence/ machine learning's role in sustainability across sectors	Qualitative, case studies	No mention found
5	Nurgul et al., 2025	Artificial Intelligence agents in renewable energy	Intelligence's role in renewable energy adoption and transition barriers	Qualitative, literature/policy review	Global
6	Azhar et al., 2025	Artificial Intelligence in Green Human Resource Management (hospitality)	Examine Artificial Intelligence's impact on Green Human Resource Management and green performance	Quantitative, survey, structural equation modeling (SEM)	Pakistan

				Quantitative, survey, technology organization environment/technology acceptance model (TOE/TAM)	
7	Ul Haq et al., 2025	Green Artificial Intelligence in small and medium enterprise sustainability	Investigate drivers/barriers of Green Artificial Intelligence in small and medium enterprises		Pakistan
8	Verdecchia et al., 2023	Systematic review of Green Artificial Intelligence	Map Green Artificial Intelligence research, trends, and energy savings Survey environmental/ economic challenges of large language models	Systematic review	No mention found
9	Singh et al., 2024	Sustainability in large language models	Assess environmental sustainability in machine learning conference papers	Systematic review	No mention found
10	Masciari et al., 2025a Różycki et al., "Energy-Aware Machine Learning Models"	Sustainability awareness in machine learning research		Systematic review, classification	Global (conferences)
11		Energy consumption in machine learning	Review strategies for energy-efficient machine learning and hardware	Systematic review	Global
12	Alzoubi et al., 2024	Green Artificial Intelligence initiatives	Identify and analyze green Artificial Intelligence initiatives/tools	Systematic review, thematic	Global
13	Ayyash & Salah, 2025	Artificial Intelligence in university energy management	Examine Artificial Intelligence adoption for energy management in higher education	Quantitative, survey, structural equation modeling (SEM)	Palestine
14	Yang et al., 2024	Artificial Intelligence and enterprise energy management	Assess Artificial Intelligence's impact on carbon emissions in Chinese firms	Quantitative, text mining, econometrics	China
15	Mu et al., "Artificial Intelligence and Its	Artificial Intelligence's environmental impact	Synthesize research on Artificial Intelligence's carbon footprint and mitigation	Mixed methods, literature review	Global

Carbon Footprint”

16	Yu et al., 2025 Ueda et al., ”Review/Research, New developments & Artificial Intelligence”	Artificial Intelligence and green governance in firms	Impact of Artificial Intelligence adoption on green governance in enterprises	Quantitative, regression	China
17		Artificial Intelligence and climate in healthcare	Review Artificial Intelligence's environmental impact in healthc	Systematic review	Global
18	Zhong & Song, 2024	Artificial Intelligence and green innovation in firms	Impact of Artificial Intelligence on green innovation capability	Quantitative, regression, mediation	China
19	Barbierato & Gatti, 2024	Red vs. Green Artificial Intelligence	Survey environmental impact of Artificial Intelligence architectures	Systematic review, clustering	No mention found
20	Anand et al., 2024	Green Artificial Intelligence in agriculture/biology	Bibliometric analysis of Green Artificial Intelligence in agriculture/biology	Bibliometric, network analysis	Global
21	Clemm et al., 2024	Green Artificial Intelligence status and future	Life-cycle-based assessment of Green Artificial Intelligence	Systematic review, life cycle assessment (LCA)	Global/European Union focus
22	Tabbakh et al., 2024	Framework for Green Artificial Intelligence	Propose comprehensive Green Artificial Intelligence framework	Systematic review, theoretical	No mention found

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23	Weng, 2025	Artificial Intelligence and environmental, social, and governance (ESG) in manufacturing	Analyze Artificial Intelligence's effect on environmental, social, and governance via green innovation	Quantitative, regression	China
24	Masciari et al., 2025b	Environmental impact of Artificial Intelligence tasks	carbon dioxide equivalent (CO2e) assessment of Artificial Intelligence	Quantitative, experimentation	Italy
25	Bolón-Canedo et al., 2024	Review of Green Artificial Intelligence	Review green Artificial Intelligence for sustainability	Systematic review	Europe (European Union focus)
26	orgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Life cycle assessment of Artificial Intelligence data centers	Assess carbon footprint of Artificial Intelligence data centers	Life cycle assessment (LCA), modeling	France, Europe, Germany
27	Chaudhary et al., 2025	Energy-efficient Artificial Intelligence Training Green Artificial Intelligence models	Green Artificial Intelligence for sustainable digital future	Qualitative review	Europe
28	Alswaitti et al., 2024	Programming language energy use in Artificial Intelligence	Data-centric energy-efficient training	Quantitative, experiments	No mention found
29	Marini et al., 2024	Impact of language choice on Artificial Intelligence energy use	Impact of language choice on Artificial Intelligence energy use	Empirical experiment	No mention found
30	Cruz et al., 2025	Convergence of software engineering and Green Artificial Intelligence in software engineering	Convergence of software engineering and Green Artificial Intelligence	Qualitative, position	No mention found
31	Martin & Sharma, 2025	Sustainable Artificial Intelligence in India	Sustainable Artificial Intelligence adoption in Ind	Qualitative, literature review	India

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32	Raman et al., 2024	Green/sustainable Artificial Intelligence research	Thematic/topic modeling of Green Artificial Intelligence literature	Systematic review, topic modeling	Global
33	Dash, 2025	Green Artificial Intelligence in enterprise systems	Framework for energy-efficient Artificial Intelligence in enterprise	Quantitative, experiments	No mention found
34	Liu, 2025	Green Artificial Intelligence in art/design	Artificial Intelligence for sustainable art/product design	Mixed methods, case studies	No mention found
35	Sowrirajan et al., 2025	Green Artificial Intelligence for carbon reduction	Green Artificial Intelligence project for carbon dioxide reduction	Quantitative, machine learning models	No mention found

Regarding the Methodology used in the above studies, 15 studies used systematic review or related methods, including bibliometric, thematic, life cycle assessment, topic modeling, clustering, classification, network analysis, and theoretical approaches), 12 studies used quantitative methods, including surveys, regression, econometrics, experiments, machine learning models, text mining, structural equation modeling, and technology-organization-environment/technology acceptance model). 5 studies used qualitative methods, including case studies, literature/policy review, and position papers. 2 studies used mixed methods and one study used empirical experiment as its primary methodology.

Regarding the Geographic Context, 11 studies were conducted in a global context or had a global focus, 5 studies were conducted in China, 2 studies were conducted in Pakistan, 1 study was conducted in India, 5 studies were conducted in Europe, including studies focused on the European Union, France, Germany, and Italy, some studies included multiple European countries. One study had a United States/United Kingdom focus within a global context, one study was conducted in Palestine. One study was conducted in an urban context (no further details were found). Finally, I did not find mention of the geographic context for 11 studies.

4.1.2 Thematic Analysis

Several of the literature sources listed above mention convergence on the fundamental principles of green artificial intelligence, with a focus on energy efficiency, carbon dioxide reduction, and material sustainability. Some works include broader concepts of sustainability, engagement, and ethics such as transparency, fairness, and alignment with United Nations Sustainable Development Goals into their definitions of green artificial intelligence. Other terms such as “sustainable artificial intelligence,” “environmentally friendly artificial intelligence,” or “green artificial intelligence” are some of the commonly are often used without clear distinction. There are works such as Ul Haq et al., 2025; Cruz et al., 2025, which focus on integrating with organizational innovation and policy, while there are works such as Marini et al., 2024, that highlighted more of its technical concepts like programming language efficiency. There are works such as Verdecchia et al., 2023; Clemm et al., 2024, which emphasize more on a life-cycle viewpoint by accounting for both operational and embedded emissions of green artificial intelligence with broader goals of environmental and social sustainability.

4.1.2.1 Environmental Impact Assessment Frameworks and Metrics (*table 3*)

Study	Framework/Metric Type	Assessment Scope	Measurement Approach	Validation Status
1 Alswaitti et al., 2024	Energy consumption (Joules)	Training	CodeCarbon library	Empirical validation
2 Ranpara, 2025	Energy, carbon, material recovery	Deployment, operations	Life Cycle Assessment, Internet of Things sensors	Empirical validation
3 Alzou et al., 2025	Energy, carbon, hardware efficiency	Training, inference, deployment	CodeCarbon, Experiment Impact Tracker	Empirical, sectoral
4 Marini et al., 2024	Energy, carbon (Joules, carbon dioxide)	Training, inference	CodeCarbon	Empirical validation

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5	Hasan et al., 2025	Energy, carbon (tons carbon dioxide equivalent)	Training, inference, deployment, disposal	Multiple tools (CodeCarbon, Carbontracker, etc.)	Review, case examples
6	Verdecchia et al., 2023	Energy efficiency, carbon footprint	Training, inference	Lab experiments	Review, summary statistics
7	Masciari et al., 2025	Carbon dioxide equivalent emissions (kg)	Training, inference	Custom equation	Empirical validation
8	Singh et al., 2024	Energy, carbon, hardware efficiency	Training, inference, deployment	LLMCarbon framework	Case study
9	Ul Haq et al., 2025	Energy, carbon, emissions trackin	No mention found	Real-time tracking	Survey, sectoral
10	Masciari et al., "Assessing Awareness"	Energy, carbon	Full lifecycle	Standardized reporting, CodeCarbon	Bibliometric analysis
11	Różycki et al., "Energy-Aware Models"	Energy, carbon, hardware efficiency	Training, deployment	Machine Learning Emissions Calculator	Review, estimates
12	Sumathi and Devilakshmi, "Green AI Innovations"	Carbon, energy	Full lifecycle	Greenhouse Gas Protocol, Carbon Footprint Calculator	Review
13	Alzoubi et al., 2024	Energy (megawatt-hours), carbon dioxide (tons)	Training, inference, deployment Development to deployment	Cloud platform tools	Review, case examples
14	Raman et al., 2024	Energy, carbon	deployment	Model training, hardware design	Review, estimates
15	Dash, 2025	Energy, carbon (kilowatt-hours)	Training, inference	PowerLogic meters, International Energy Agency factors	Empirical validation
16	Mu et al., "AI and Carbon Footprint"	Energy, carbon (tons, gigawatt-hours)	Training, deployment	Eco2AI, tracking tools	Review, case examples
17	Barbierato and Gatti, 2024	Energy, carbon, hardware efficiency	Training, inference, deployment	Estimation, sparsity	Review
18	Clemm et al., 2024	Energy, carbon (kg carbon dioxide equivalent, floating point operations per second)	Manufacturing, use, disposal	Life Cycle Assessment, carbon footprinting	Case study

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19	Tabbakh et al., 2024	Energy (watt-hours), carbon	Training, inference	Pruning, quantization	Case studies
20	Ueda et al., "Review/Research"	Energy, carbon	Training, inference, deployment, disposal	Compression, quantization	Review, estimates
21	Orgeval et al., "Carbon Footprint of AI Data Centers"	Carbon, energy	Manufacturing, use	Life Cycle Assessment, Carbontracker	Case study
22	Bolón-Canedo et al., 2024	Energy, carbon, hardware efficiency	Training	CarbonTracker, CodeCarbon	Review
23	Chaudhary et al., 2025	Energy (megawatt-hours), carbon (tons)	Training, deployment	Carbon Tracker, CodeCarbon	Review
24	Martin and Sharma, 2025	Energy, carbon, water, electronic waste	Training, deployment	Estimates, sectoral data	Policy analysis
25	Cruz et al., 2025	Energy, carbon, hardware efficiency	Development, training, usage, inference, retirement	Monitoring tools, documentation	Conceptual
26	Ayyash and Salah, 2025	Energy efficiency, carbon	No mention found	Artificial intelligence-driven data collection	Survey
27	Yang et al., 2024	Carbon emission intensity	No mention found	Emissions/costs/assets	Econometric analysis
28	Sowrirajan et al., 2025	Carbon, energy	No mention found	User data analysis	Project case study
29	Azhar et al., 2025	No mention found	No mention found	No mention found	Survey
30	Yu et al., "AI and Green Governance"	No mention found	No mention found	No mention found	Econometric analysis
31	Anand et al., 2024	No mention found	No mention found	No mention found	Bibliometric analysis
32	Liu, 2025	Material waste, energy, carbon, recyclability	Raw material, disposal, recycling	Artificial intelligence monitoring, Life Cycle Assessment	Case studies
33	Weng, 2025	Energy, emissions	No mention found	No mention found	Text analysis
34	Nurgul et al., 2025	No mention found	No mention found	No mention found	Qualitative synthesis
35	Zhong and Song, 2024	No mention found	No mention found	No mention found	Econometric analysis

Frameworks and Metrics: 28 studies assessed energy and 28 assessed carbons 7 studies included hardware efficiency, 2 studies included material/waste, 1 study each included water, electronic waste, emissions (general), and recyclability. I didn't couldn't find a specified framework or metric type in 5 studies.

Assessment Scope: Training was included in 18 studies, Inference in 12 studies, deployment in 12 studies, full lifecycle was covered in 2 studies, manufacturing in 2 studies, disposal in 4 studies, development in 2 studies and other stages (operations, use, recycling, usage, retirement) were each included in 1 study. I didn't find the assessment scope specified in 10 studies.

Measurement Approaches: Code Carbon was used in 7 studies, Carbon Tracker in 4 studies, Life Cycle Assessment in 4 studies, Custom estimation or modeling approaches in 9 studies, Artificial intelligence-driven/monitoring/user data approaches in 5 studies, Pruning/quantization/compression in 2 studies, Cloud/platform tools in 1 study, Greenhouse Gas Protocol/Carbon Footprint Calculator in 2 studies, Other approaches (lab experiments, standardized reporting, Eco2AI, multiple tools) each found in 1 study. I didn't find the measurement approach specified in 6 studies.

Validation Status: 6 studies used empirical validation, 11 were reviews, 6 used case studies or case examples, 3 surveys, 2 bibliometric analyses, 3 econometric analyses, 1 policy analysis, 1 conceptual study, 1 qualitative synthesis, 1 text analysis, 1 project case study, 3 using summary statistics or estimates. All studies had some form of validation or study design. I didn't find any studies without a validation status

4.1.2.2 Adoption Frameworks and Influencing Factors

Barriers and Resistance to Green Artificial Intelligence Implementation

The selected studies describe a range of conceptual and practical frameworks for Green artificial intelligence adoption, including evolutionary sampling, multi-layered optimization, Technology-Organization-Environment and Technology Acceptance Model (TOE-TAM) integration, and sector-specific models, e.g., for healthcare, small and medium-sized enterprises, data centers (Verdecchia et al., 2023; Haq et al., 2025; Clemm et al., 2024). **Influencing factors** are consistently categorized into, (1) Technological (Marini et al., 2024): Algorithm/hardware efficiency, programming

languages, (2) Organizational: Resources, leadership, culture, capabilities and (3) Environmental: Regulations, market/stakeholder pressures (Marini et al., 2024; Verdecchia et al., 2023).

There are several Factors outlined in the literature that foster the adoption and implementation of Green AI, including establishing common standards for Green AI across different industries, the use of open-source tools, utilizing cloud-based infrastructure and services and obtaining leadership involvement (Clemm et al., 2024). Significant barriers remain to Fully implementing Green AI across all Industries. These barriers arise from the increased technical complexity associated with implementing Green AI, the elevated Costs for implementing and integrating Green AI, a deficiency in Specialized Skills in all areas of Green AI, a lack of Ambiguity in regulatory Frameworks and an overall lack of awareness amongst the multiple Stakeholders that must be included to Fully implement Green AI (Verdecchia et al., 2023, Haq et al., 2025). Most recently, Evidence from numerous Authors cited above has shown the value of Creating Lifecycle-Based Management Frameworks, such as those created by UI Haq et al. and Cruz et al., to successfully integrate Multiple Factors that Foster Successful Overall Implementations of Green AI and the necessity of Coordinating Stakeholders and Policy in order to Successfully implement Multiple Stakeholder Lifecycle-Based Management Frameworks to successfully Implement Green AI across all Industries.

Different types of barriers arise during the adoption of green AI practices as mentioned in the above articles such as, (1) Technical Barriers: Energy-intensive algorithms, lack of energy-efficient tools, hardware limitations (Verdecchia et al., 2023; Clemm et al., 2024), (2) Economic Barriers: High costs, infrastructure deficits, financial constraints, especially in resource-constrained settings (Haq et al., 2025) and (3) Organizational Barriers: Culture, leadership, expertise, change management (Haq et al., 2025; Verdecchia et al., 2023), (4) Regulatory Barriers: Policy gaps, lack of standards, insufficient enforcement (Verdecchia et al., 2023). (5) Awareness and Transparency: Limited awareness, lack of transparency, and absence of standardized reporting further exacerbate resistance (Verdecchia et al., 2023; Alzoubi & Mishra, 2024).

To address and balance the above barriers, some enablers are proposed, such as, Leadership commitment, financial incentives, open-source initiatives, and cross-sectoral collaboration (Clemm et al., 2024). Several selected studies identify barriers that align with Innovation Resistance Theory, encompassing technical, economic, organizational, and regulatory resistance (Verdecchia et al., 2023, Haq et al., 2025, Alzoubi & Mishra, 2024).

4.1.2.3 Policy and Governance Framework Gaps

Many studies highlight the need for European Union and global **standards**, especially in sustainability reporting, lifecycle-based governance, and integration of ethical and social criteria (Verdecchia et al., 2023). Although the European Union Artificial Intelligence Act is frequently cited as a significant regulatory advancement, several studies note its limitations of specific key performance indicators and methodologies for sustainability reporting (Verdecchia et al., 2023). In response, several studies advocate comprehensive regulatory frameworks, public-private partnerships, and international collaboration (Alzoubi & Mishra, 2024; Clemm et al., 2024; Cruz et al., 2025). Regarding ethical Considerations, transparency, fairness, privacy, and inclusivity are increasingly recognized as essential components of Green artificial intelligence governance, though practical implementation remains limited (Verdecchia et al., 2023; Alzoubi & Mishra, 2024).

4.1.2.4 Lifecycle-Based Integration Approaches (table 4)

	Study	Lifecycle Stage	Framework Components	Implementation Considerations	Policy Implications
1	Alswaitti et al., 2024	Training	Evolutionary sampling, energy efficiency	Stage-specific, shared repository	Emphasis on collaboration, resource conservation
2	Ranpara, 2025	Design, development, deployment, maintenance	Multi-layered optimization, Internet of Things, Life Cycle Assessment	Lifecycle-based, modular, scalable	Alignment with United Nations Sustainable Development Goals

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3	Alzou et al., 2025	Design, development, deployment, maintenance	Holistic/structured frameworks, PRISMA	Lifecycle-based, healthcare focus	Need for global standards, European Union Artificial Intelligence Act Trade-off between efficiency and ease
4	Marini et al., 2024	Training, inference	Programming language/algorithm efficiency	Stage-specific, empirical	Policy blueprint for carbon neutrality
5	Hasan et al., 2025	Development to disposal	GREENSOFT, Life Cycle Assessment, multiple tools	Lifecycle-based, review	Need for comprehensive lifecycle coverage
6	Verdecchia et al., 2023	Training, inference	Data extraction, Green artificial intelligence definition	Stage-specific, review	Responsible artificial intelligence design/deployment
7	Masciari et al., 2025	Training, manufacturing, disposal	Carbon dioxide equivalent equation, Energy Hardware-Based Data Aggregation cluster	Lifecycle-based, empirical	Emphasis on lifecycle assessments
8	Singh et al., 2024	Training, deployment, retirement	Lifecycle optimization, modular design Technology-Organization-Environment and Technology	Lifecycle-based, large language models	Standardized compliance, incentives
9	Ul Haq et al., 2025	Design, development, deployment, maintenance	Acceptance Model, Green Investment, Green Supply Leadership	Lifecycle-based, small and medium-sized enterprises	Need for lifecycle assessment
10	Masciari et al., "Assessing Awareness"	Training	Standardized reporting, emissions tools	Stage-specific, machine learning research	Industry-wide standards needed
11	Różycki et al., "Energy-Aware Models"	Design to maintenance	Green Power Optimization and Energy Optimization, model compression, hardware	Lifecycle-based, machine learning pipelines	Policy incentives, global standards
12	Sumathi and Devilakshmi, "Green AI Innovations"	Design to disposal	Green artificial intelligence framework, lifecycle focus	Lifecycle-based, cross-sector	

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13	Alzoubi et al., 2024	Development, deployment, maintenance	Categorization of initiatives	Thematic, not lifecycle-based	Need for government policy
14	Raman et al., 2024	Development, training, deployment	SHIFT, energy-efficient hardware	Lifecycle-based, thematic	Need for global frameworks
15	Dash, 2025 Mu et al., "AI and Carbon Footprint"	Training, inference	Optimization framework	Stage-specific, enterprise	Scalability, cost efficiency Artificial intelligence carbon taxes, standards
16	Barbierato and Gatti, 2024	Design to deployment	Carbon tracking, optimization	Lifecycle-based, technology industry	
17		Design to disposal	Red/Green artificial intelligence survey, clustering	Lifecycle-based, review	Policy, risk assessment
18	Clemm et al., 2024	Model/hardware lifecycle	System thinking, Life Cycle Assessment, Artificial Intelligence for Green Artificial Intelligence	Lifecycle-based, data centers	European Union regulations, flexible policy Tax incentives, reporting mandates Regulatory frameworks, global initiatives
19	Tabbakh et al., 2024	Design to maintenance	Model optimization, efficient hardware	Lifecycle-based, case studies	
20	Ueda et al., "Review/Research"	Design to disposal	Eco-design, lifecycle assessment Life Cycle Assessment, Activity-based Carbon Tracking, Product and Activity Impact Assessment, Product Environmental Profile	Lifecycle-based, healthcare	
21	Orgeval et al., "Carbon Footprint of AI Data Centers"	Manufacturing, use, end-of-life		Lifecycle-based, data centers	Holistic emissions assessment
22	Bolón-Canedo et al., 2024	Design to deployment	Green artificial intelligence strategies, assessment tools	Lifecycle-based, review	European Union Artificial Intelligence Act, regulatory sandboxes

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			Green-by/in artificial intelligence, Assessment List for Trustworthy Artificial Intelligence, European Union policy		European Union Artificial Intelligence Act, codes of conduct
23	Chaudhary et al., 2025	Design to deployment		Lifecycle-based, review	
24	Martin and Sharma, 2025	Training to disposal	Stepwise integration, Public-Private Partnerships	Lifecycle-based, India	Need for regulations, Public-Private Partnerships
25	Cruz et al., 2025	Design to disposal	Data/model/system centric, Identification Car Technology Acceptance Model 2, Technology Readiness Index, Resource-Based View, Diffusion of Innovation	Lifecycle-based, software engineering/ artificial intelligence	European Union Artificial Intelligence Act, documentation guidelines
26	Ayyash and Salah, 2025	Adoption, implementation	Research framework, mediation	Lifecycle-based, higher education	National guidelines, incentives
27	Yang et al., 2024	Development, deployment, maintenance	Green artificial intelligence project, functionalities	Stage-specific, China	Government incentives, monitoring
28	Sowrirajan et al., 2025	Design, development	Ability, Motivation, Opportunity framework, Green Human Resource Management	Stage-specific, project	User-centric, future advancements
29	Azhar et al., 2025	Deployment	Resource-Based View, green governance	Stage-specific, hospitality	Incentives, training
30	Yu et al., "AI and Green Governance"	Development, deployment, maintenance	Bibliometric, decision support	Stage-specific, China	Dual carbon goals, firm investment
31	Anand et al., 2024	Deployment, maintenance, training	Integral model, artificial intelligence-based framework	Stage-specific, agriculture	Subsidies, partnerships
32	Liu, 2025	Design to maintenance		Lifecycle-based, creative	Need for energy-efficient models

33	Weng, 2025	Design to maintenance	Environmental, Social, and Governance integration, innovation	Stage-specific, manufacturing	Incentives, Environmental, Social, and Governance disclosure
34	Nurgul et al., 2025	Design, deployment, maintenance	Artificial intelligence agents, comprehensive framework	Lifecycle-based, energy	Transparency, regulatory alignment
35	Zhong and Song, 2024	No explicit mention found; firm lifecycle focus	Mediation analysis, green innovation	Firm lifecycle-based, China	Targeted incentives, green finance

Regarding life cycle-based integration approaches, 23 studies addressed the full or multiple stages of the artificial intelligence system lifecycle “lifecycle-based”, 12 studies focused on specific stages such as training, deployment, or maintenance “stage-specific”.

Regarding Thoughts on Implementation, 23 studies described their approach as lifecycle-based, 2 studies described stage-specific approaches, 5 studies were reviews, 2 were empirical, and 2 were thematic. Sectoral focus was noted in several studies, as healthcare (2) , small and medium-sized enterprises (1) , machine learning pipelines (1), cross-sector (1), technology industry (1), data centers (2), India (1), software engineering/artificial intelligence (1) , higher education (1) , China (3) , project (1) , hospitality (1) , agriculture (1), creative (1) , manufacturing (1) , and energy (1).

About Policy Implications, 5 studies discussed the need for global standards or frameworks, including United Nations Sustainable Development Goals and global initiatives. 5 studies referenced the European Union Artificial Intelligence Act or other European Union policy/regulation. 7 studies discussed incentives, including tax incentives, government incentives, and targeted incentives, 4 studies emphasized the need for lifecycle assessment or comprehensive lifecycle coverage. 3 studies mentioned industry or national guidelines or codes of conduct, 2 studies discussed trade-offs, such as efficiency vs. ease or cost efficiency, 2 studies

addressed carbon neutrality or dual carbon goals, 2 studies discussed documentation or reporting requirements, 2 studies mentioned regulatory sandboxes or flexible policy, Other policy themes included risk assessment (1), responsible artificial intelligence (1), transparency (1), collaboration/resource conservation (1), subsidies/partnerships (1), monitoring (1), Environmental, Social, and Governance disclosure (1), Public-Private Partnerships (1), green finance (1), investment (1), usercentric/future advancements (1), and training (1). I didn't find policy implications for some studies, and some studies were counted in multiple policy categories.

4.1.2.5 Organizational Drivers of Green Artificial Intelligence Adoption (table 5)

Study		Key Organizational Drivers
1	Ranpara, 2025	Stakeholder engagement, structured decision-making, modular/scalable frameworks
2	Alzou et al., 2025	Leadership support, resource allocation, integration into workflows
3	Hasan et al., 2025	Policy blueprints, cross-sector collaboration
4	Sumathi & Devilakshmi, "Green Artificial Intelligence"	Collaboration across academia, industry, government
5	Nurgul et al., 2025	Leadership support, strategic attention to marketing/ethics
6	Azhar et al., 2025	Leadership support, employee readiness, organizational culture
7	Ul Haq et al., 2025	Organizational readiness, change management, leadership commitment
8	Verdecchia et al., 2023	Collaborative culture, industry-academic partnerships
9	Singh et al., 2024	Leadership support, cultural shift, life cycle assessment
10	Masciari et al., 2025a	Cultural/procedural change, leadership for sustainability
11	Rózycki et al., "Energy-Aware Machine Learning Models"	Leadership support, resource allocation, sustainability culture
12	Alzoubi et al., 2024	Leadership support, resource allocation
13	Ayyash & Salah, 2025	Strategic partnerships, policy incentives, awareness programs

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14	Yang et al., 2024	Governance, compliance, research and development focus
15	Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Corporate pledges, leadership support
16	Yu et al., 2025	Leadership in traditional manufacturing, resource allocation
17	Ueda et al., "Review/Research, New developments & Artificial Intelligence"	Collaboration, knowledge sharing
18	Zhong & Song, 2024	Reduced agency costs, managerial incentives
19	Barbierato & Gatti, 2024	Leadership support, resource allocation
20	Anand et al., 2024	Leadership, data security, collaboration
21	Clemm et al., 2024	Life cycle thinking, governance, research and development support
22	Tabbakh et al., 2024	Leadership, resource allocation
23	Weng, 2025	Revenue growth, research and development, environmental, social, and governance integration
24	Masciari et al., 2025b	Protocols, energy efficiency certification
25	Bolón-Canedo et al., 2024	Cost savings, efficiency, leadership
26	'orgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Leadership, resource allocation
27	Chaudhary et al., 2025	Leadership, resource allocation
28	Alswaitti et al., 2024	Leadership, collaboration
29	Marini et al., 2024	Leadership, resource allocation
30	Cruz et al., 2025	Software engineering community leadership, education
31	Martin & Sharma, 2025	Leadership, public-private partnerships
32	Raman et al., 2024	Leadership, ethical guidelines
33	Dash, 2025	Leadership, resource allocation
34	Liu, 2025	Leadership, resource allocation

35 Sowrirajan et al., 2025 Leadership, resource allocation

Key **organizational drivers** identified across all the above 35 studies, specifically, Leadership support or commitment reported in 24 studies, resource allocation or organizational/employee readiness mentioned in 14 studies. Collaboration or partnership (cross-sector, industry-academic, public-private) mentioned in 9 studies. Organizational culture or cultural/procedural change are reported in 5 studies, Policy, governance or compliance drivers, are mentioned in 6 studies. Research and development or innovation focus, marketing, ethics, or environment, social and governance integration, structured decision-making, frameworks, or life cycle thinking, cost savings, efficiency or revenue growth mentioned in 3 studies. Education or awareness programs, certification or corporate pledges, managerial incentives or agency cost reduction reported in 2 studies. Other drivers like stakeholder engagement, integration into workflows, change management and data security reported in 4 studies. All studies in the above table No. 4 included at least one organizational driver.

4.1.2.6 Technological Drivers (*table 6*)

Study	Key Technological Drivers
1 Ranpara, 2025	Scalability, modularity, energy-efficient algorithms
2 Alzou et al., 2025	Model compression, edge computing, telemedicine platforms
3 Hasan et al., 2025	Transfer learning, federated learning, hardware innovation
4 Sumathi & Devilakshmi, "Green Artificial Intelligence"	Energy-efficient algorithms, low-power hardware
5 Nurgul et al., 2025	Artificial Intelligence for decision support, Internet of Things/smart grid integration
6 Azhar et al., 2025	Employee readiness, infrastructure, Artificial Intelligence capabilities
7 UI Haq et al., 2025	Perceived ease of use/usefulness, Artificial Intelligence algorithms
8 Verdecchia et al., 2023	Technological readiness, tool maturity

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9	Singh et al., 2024	Solar-powered Artificial Intelligence, modular architectures
10	Masciari et al., 2025a	Standardized reporting, sustainable algorithms
11	Różycki et al., "Energy-Aware Machine Learning Models"	Model compression, pruning, quantization, hardware
12	Alzoubi et al., 2024	Technical know-how, tool functionality
13	Ayyash & Salah, 2025	Digital infrastructure, Artificial Intelligence capabilities
14	Yang et al., 2024	Technological innovation, resource allocation
15	Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Pruning, quantization, knowledge distillation
16	Yu et al., 2025	Data analytics, automation systems
17	Ueda et al., "Review/Research, New developments & Artificial Intelligence"	Energy-efficient models, green computing
18	Zhong & Song, 2024	Information processing, monitoring
19	Barbierato & Gatti, 2024	Infrastructure, energy-efficient development
20	Anand et al., 2024	Data-driven insights, predictive analytics
21	Clemm et al., 2024	Life cycle approach, practical tools
22	Tabbakh et al., 2024	Energy-efficient hardware, cloud Artificial Intelligence
23	Weng, 2025	Data acquisition, innovation
24	Masciari et al., 2025b	Artificial Intelligence accelerators, cloud-based approaches
25	Bolón-Canedo et al., 2024	Algorithm/hardware optimization
26	Forgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Infrastructure for environmental assessment
27	Chaudhary et al., 2025	Cloud/edge computing, green algorithms
28	Alswaitti et al., 2024	Energy-efficient infrastructure
29	Marini et al., 2024	Technological readiness, energy-efficient languages
30	Cruz et al., 2025	Research frameworks, sustainable software engineering
31	Martin & Sharma, 2025	Artificial Intelligence infrastructure, readiness

32	Raman et al., 2024	Energy-efficient computing, hardware
33	Dash, 2025	Optimization algorithms, scalability
34	Liu, 2025	Artificial Intelligence technologies, energy-efficient protocols
35	Sowrirajan et al., 2025	Artificial Intelligence/data-driven integration

Most of the above studies included multiple **technological drivers** within the following categories across of the total 35 studies: **Algorithmic innovation** like model compression, pruning, quantization, transfer/federated learning, optimization algorithms, AI/data driven integration, AI algorithms/technologies/capabilities, automation systems, predictive analytics, data driven insights, information processing, resource allocation, modularity, scalability, and sustainable algorithms are reported in 28 studies. **Hardware and Infrastructure**, as for hardware, low-power hardware, energy-efficient hardware, AI accelerators, infrastructure including digital, AI and cloud infrastructure, tool maturity/functionality, practical tools, cloud/edge computing are mentioned in 24 studies. Regarding **energy efficiency**, such as energy-efficient algorithms, models, hardware, infrastructure, protocols, languages, green computing, green AI, green algorithms, energy-aware approaches, low-power hardware, solar-powered AI, sustainable algorithms and sustainable software engineering, 19 studies mentioned these topics. **Readiness and human/organizational** factors are mentioned in 6 studies. These factors refer to employee readiness, perceived ease of use/usefulness, technological readiness and technical know-how. Internet of Things/smart grid integration and related drivers such as telemedicine platforms, monitoring and data acquisition are mentioned in 4 studies. **Reporting, frameworks and standardizations** such as standardized reporting, research frameworks, lifecycle approaches, practical tools and sustainable software engineering referred in 5 studies. Finally, 2 studies report on environmental assessment and solar-powered Artificial Intelligence.

4.1.2.6 Environmental Drivers (table 7)

	Study	Key Environmental Drivers
1	Ranpara, 2025	United Nations Sustainable Development Goals alignment, environmental preservation
2	Alzou et al., 2025	Carbon reduction, energy consumption
3	Hasan et al., 2025	Regulatory pressure, sustainability goals
4	Sumathi & Devilakshmi, "Green Artificial Intelligence"	Regulations, government incentives
5	Nurgul et al., 2025	Sustainability goals, regulatory pressure
6	Azhar et al., 2025	Sustainability goals, regulatory pressure
7	Ul Haq et al., 2025	Regulatory pressure, market demands
8	Verdecchia et al., 2023	No explicit mention, but implied
9	Singh et al., 2024	Regulatory pressure, environmental challenges
10	Masciari et al., 2025a	Regulatory pressure, sustainability goals
11	Różycki et al., "Energy-Aware Machine Learning Models"	Regulatory pressure, sustainability goals
12	Alzoubi et al., 2024	Regulatory pressure, sustainability goals
13	Ayyash & Salah, 2025	Sustainability goals, green campus initiatives
14	Yang et al., 2024	Government incentives, regulatory pressure
15	Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Regulatory pressure, sustainability standards
16	Yu et al., 2025	Regional infrastructure, market competition
17	Ueda et al., "Review/Research, New developments & Artificial Intelligence"	Policy/governance frameworks, sustainability goals
18	Zhong & Song, 2024	Green innovation, sustainability goals
19	Barbierato & Gatti, 2024	Regulatory pressure, sustainability goals
20	Anand et al., 2024	Sustainability goals, environmental awareness
21	Clemm et al., 2024	Regulatory pressure, sustainability goals

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22	Tabbakh et al., 2024	Global sustainability goals, regulatory pressure
23	Weng, 2025	Environmental, social, and governance integration, green innovation
24	Masciari et al., 2025b	Policy recommendations, environmental challenges
25	Bolón-Canedo et al., 2024	European Union Artificial Intelligence Act, regulatory pressure
26	'orgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Regulatory pressure, sustainability goals
27	Chaudhary et al., 2025	Regulatory pressure, European Union guidelines
28	Alswaitti et al., 2024	Regulatory pressure, sustainability goals
29	Marini et al., 2024	Environmental sustainability goals
30	Cruz et al., 2025	Regulatory pressure, societal concern
31	Martin & Sharma, 2025	Regulatory pressure, sustainability goals
32	Raman et al., 2024	Regulatory pressure, United Nations Sustainable Development Goals
33	Dash, 2025	Sustainability as strategic priority
34	Liu, 2025	Environmental challenges, carbon reduction
35	Sowrirajan et al., 2025	United Nations Sustainable Development Goals, carbon reduction

Across the above 35 studies the most frequently cited **environmental drivers** were regulatory pressure and sustainability goals. Specifically, regulatory pressure aspects like regulations, policy, European Union Artificial Intelligence Act and European Union guidelines, were reported in 21 studies. 18 studies reported sustainability goals aspects which refer to global/environmental/strategic/standards sustainable goals. United Nations Sustainable Development goals, carbon reduction issues and environmental challenges mentioned in 3 studies, different for each category. 2 studies for each category report government incentives, market demands or competition, green innovation and policy/governance frameworks or recommendations. The following topics, energy consumption, green campus initiatives, regional infrastructure, environmental, social and governance integration, environmental preservation, environmental awareness and societal concern are

mentioned once per study. In the study of Verdecchia et al., 2023, no explicit environmental drivers were found.

4.1.2.7 Barriers to Green Artificial Intelligence Adoption

Organizational Barriers (table 8)		Key Organizational Barriers
Study		
1	Ranpara, 2025	Lack of cross-disciplinary collaboration
2	Alzou et al., 2025	Resource constraints, impacts on clinical judgment
3	Hasan et al., 2025	Interdisciplinary challenges, rapid technology change
4	Sumathi & Devilakshmi, "Green Artificial Intelligence"	Need for stakeholder cooperation
5	Nurgul et al., 2025	Trust deficits, behavioral inertia
6	Azhar et al., 2025	Resistance to change, resource constraints
7	Ul Haq et al., 2025	Resource constraints, structural inefficiencies
8	Verdecchia et al., 2023	Low industrial focus, lack of expertise
9	Singh et al., 2024	No mention found
10	Masciari et al., 2025a	Lack of incentives, absence of guidelines
11	Różycki et al., "Energy-Aware Machine Learning Models"	Externalization of costs, lack of incentives
12	Alzoubi et al., 2024	Resource constraints, volunteer reliance
13	Ayyash & Salah, 2025	No mention found
14	Yang et al., 2024	No mention found
15	Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Rapid growth, ethical concerns
16	Yu et al., 2025	Resistance to change, lack of expertise
17	Ueda et al., "Review/Research, New developments & Artificial Intelligence"	Lack of policy/governance frameworks
18	Zhong & Song, 2024	Agency costs, divergent interests
19	Barbierato & Gatti, 2024	Profit focus over sustainability

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20	Anand et al., 2024	Need for collaboration
21	Clemm et al., 2024	Lack of expertise, resource constraints
22	Tabbakh et al., 2024	Resource constraints for small and medium enterprises/researchers
23	Weng, 2025	Shrinking workforce, labor shortages
24	Masciari et al., 2025b	Need for protocols, certification
25	Bolón-Canedo et al., 2024	No mention found
26	'orgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Resource constraints
27	Chaudhary et al., 2025	No mention found
28	Alswaitti et al., 2024	Need for collaboration
29	Marini et al., 2024	Balancing sustainability with other goals
30	Cruz et al., 2025	Need for inclusive ecosystems
31	Martin & Sharma, 2025	Need for public-private partnerships, job loss concerns
32	Raman et al., 2024	Governance gaps
33	Dash, 2025	Static trade-off approaches
34	Liu, 2025	Integration challenges
35	Sowrirajan et al., 2025	Performance/usability prioritized over sustainability

The most frequent **organizational barriers** across the 35 studies mentioned are resource constraints and lack of collaboration/cooperation. 8 studies mentioned resource constraints like funding, workforce, infrastructure and volunteer reliance. 6 studies mentioned lack of collaboration and cooperation as a major issue, this refers to cross-disciplinary, interdisciplinary, stakeholder, public-private partnerships. 5 studies reported industrial/structural inefficiencies such as low industrial focus, agency costs, divergent interest, profit focus. 3 studies referred each to lack of expertise/skills, resistance to change/behavioral inertia and lack of incentives, guidelines, protocols or certifications. 2 studies reported each governance and policy

gaps, trust and ethical concerns, balancing sustainability with other organizational goals, rapid technological change or growth. 5 studies mentioned other barriers like impacts on clinical judgement, need of inclusive ecosystems, job-loss concerns, static tradeoff approaches and integration challenges. 5 studies didn't mention any organizational barrier.

Technological Barriers (table 9)

Study	Key Technological Barriers
1 Ranpara, 2025	Initial computational overhead, reliance on Internet of Things/cloud
2 Alzou et al., 2025	High energy use, scalability, integration challenges
3 Hasan et al., 2025	Lack of standardized metrics, life cycle assessment challenges
4 Sumathi & Devilakshmi, "Green Artificial Intelligence"	High energy use, quantum computing challenges
5 Nurgul et al., 2025	Technical feasibility, grid integration
6 Azhar et al., 2025	Limited Artificial Intelligence adoption, readiness gaps
7 Ul Haq et al., 2025	Limited expertise, infrastructure
8 Verdecchia et al., 2023	Tool immaturity, reproducibility issues
9 Singh et al., 2024	Infrastructure gaps
10 Masciari et al., 2025a	Lack of transparency, energy-intensive algorithms
11 Różycki et al., "Energy-Aware Machine Learning Models"	Balancing performance/efficiency, metric gaps
12 Alzoubi et al., 2024	Complexity, interoperability, expertise needs
13 Ayyash & Salah, 2025	No mention found
14 Yang et al., 2024	No mention found
15 Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Fossil fuel reliance, high energy use
16 Yu et al., 2025	Infrastructure gaps, technical complexity
17 Ueda et al., "Review/Research, New developments & Artificial Intelligence"	Data/model complexity, frequent updates

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18	Zhong & Song, 2024	No mention found
19	Barbierato & Gatti, 2024	Hardware limitations, need for specialized hardware
20	Anand et al., 2024	Data privacy/security, infrastructure gaps
21	Clemm et al., 2024	Complexity of efficiency methods
22	Tabbakh et al., 2024	Scalability/accessibility for small and medium enterprises
23	Weng, 2025	Resource scarcity, environmental degradation
24	Masciari et al., 2025b	Infrastructure, complexity, interoperability
25	Bolón-Canedo et al., 2024	Accuracy prioritized over efficiency
26	'orgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Data center complexity, information gaps
27	Chaudhary et al., 2025	High processing power, rapid growth
28	Alswaitti et al., 2024	Energy use, complexity of sample selection
29	Marini et al., 2024	Technical challenges in efficient languages
30	Cruz et al., 2025	Need for supportive frameworks
31	Martin & Sharma, 2025	Infrastructure, data center gaps
32	Raman et al., 2024	High energy use, need for efficient training
33	Dash, 2025	Architecture reliance, monitoring granularity
34	Liu, 2025	Over-reliance on Artificial Intelligence, scalability
35	Sowrirajan et al., 2025	Lack of integrated functionalities

Most studies reported more than one type of **technological barrier**. Especially, energy use and environmental impact barriers reported in 13 studies, infrastructure gaps, hardware limitations and complexity or technical feasibility barriers reported in 10 studies. 7 studies mentioned scalability, integration or interoperability barriers, and 6 other articles refer to metrics, transparency or reproducibility issues. 5 studies reported expertise, adoption or readiness gaps, other 4 mentioned tools, framework

or functionality gaps and 1 study mentioned data privacy or security barriers. Furthermore, 8 studies referred to other types of barriers like quantum computing challenges, frequent updates, rapid growth, architecture reliance, monitoring granularity and over-reliance on AI. Finally, in 3 studies, I didn't find any mention of technological barriers.

Environmental Assessment Barriers (table 10)

Study	Key Environmental Assessment Barriers
1 Ranpara, 2025	Energy consumption of Artificial Intelligence models
2 Alzou et al., 2025	Energy constraints, sustainability conflicts
3 Hasan et al., 2025	Energy constraints, sustainability conflicts
4 Sumathi & Devilakshmi, "Green Artificial Intelligence"	High energy/carbon emissions
5 Nurgul et al., 2025	Grid integration challenges
6 Azhar et al., 2025	No mention found
7 Ul Haq et al., 2025	No mention found
8 Verdecchia et al., 2023	Difficulty computing climate impact
9 Singh et al., 2024	Energy/water use, emissions
10 Masciari et al., 2025a	Data center energy, cloud impact
11 Różycki et al., "Energy-Aware Machine Learning Models"	Embodied emissions, data center energy
12 Alzoubi et al., 2024	Energy constraints, carbon footprinting
13 Ayyash & Salah, 2025	No mention found
14 Yang et al., 2024	No mention found
15 Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Regional carbon burden, sustainability
16 Yu et al., 2025	No mention found
17 Ueda et al., "Review/Research, New developments & Artificial Intelligence"	Energy use, carbon footprint, electronic waste

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18	Zhong & Song, 2024	No mention found
19	Barbierato & Gatti, 2024	Need to mitigate impact, integrate renewables
20	Anand et al., 2024	No mention found
21	Clemm et al., 2024	Energy constraints, sustainability conflicts
22	Tabbakh et al., 2024	No mention found
23	Weng, 2025	Environmental degradation
24	Masciari et al., 2025b	Environmental costs of models
25	Bolón-Canedo et al., 2024	Data center energy/carbon footprint
26	'orgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Energy constraints, electricity mix
27	Chaudhary et al., 2025	No mention found
28	Alswaitti et al., 2024	Energy use, carbon footprint
29	Marini et al., 2024	No mention found
30	Cruz et al., 2025	Energy consumption, sustainability
31	Martin & Sharma, 2025	High energy/water use, electronic waste
32	Raman et al., 2024	Energy/carbon emissions
33	Dash, 2025	Increased energy consumption
34	Liu, 2025	Energy use, environmental impact
35	Sowrirajan et al., 2025	No mention found

Energy use and carbon emissions were the most frequently cited barriers in the above selected studies. Energy use, consumption or constraints were reported in 18 studies, Carbon emissions or carbon footprint were mentioned in 9 studies, sustainable conflicts or concerns were reported in 5 studies, water use issues and electronic waste matters in 2 studies. Grid integration challenges, electricity mix or need to integrate renewable energy were reported in 3 studies. General environmental degradation

issues, costs or impact reported in 5 studies and difficulty of environmental assessment or footprint mentioned in 1 study. I didn't find mention with environmental assessment barriers in 11 studies.

4.1.2.8 Regulatory Frameworks and Policy Implications Current

Regulatory Landscape (table 11)

Study	Key Findings on Regulatory Landscape
1 Ranpara, 2025	No mention found
2 Alzou et al., 2025	European Union Artificial Intelligence Act, International Telecommunication Union, World Health Organization, United States Food and Drug Administration; energy reporting required
3 Hasan et al., 2025	Need for frameworks, Sustainable Computing for Artificial Intelligence Systems, Green Software, policy gaps
4 Sumathi & Devilakshmi, "Green Artificial Intelligence"	Stricter standards, public-private partnerships
5 Nurgul et al., 2025	Emphasis on transparency, United Nations Sustainable Development Goals, need for governance
6 Azhar et al., 2025	No mention found
7 Ul Haq et al., 2025	Inconsistent enforcement, need for standardization
8 Verdecchia et al., 2023	European Union/United Nations Framework Convention on Climate Change policies, need for evidence-based policy
9 Singh et al., 2024	General Data Protection Regulation, Health Insurance Portability and Accountability Act compliance
10 Masciari et al., 2025a	Need for standardized reporting, policy gaps
11 Różycki et al., "Energy-Aware Machine Learning Models"	No mention found
12 Alzoubi et al., 2024	No specific laws, European Union proactive, global standards
13 Ayyash & Salah, 2025	United Nations Sustainable Development Goals, Talloires Declaration, need for guidelines
14 Yang et al., 2024	Need for incentive policies, government supervision
15 Mu et al., "Artificial Intelligence and Its Carbon Footprint"	Artificial Intelligence carbon taxes, industry standards
16 Yu et al., 2025	Compliance with environmental regulations

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17	Ueda et al., "Review/Research, New developments & Artificial Intelligence"	General Data Protection Regulation, California Consumer Privacy Act, World Health Organization, International Telecommunication Union, United Nations Sustainable Development Goals
18	Zhong & Song, 2024	No mention found
19	Barbierato & Gatti, 2024	Institute of Electrical and Electronics Engineers, Organisation for Economic Co-operation and Development, need for Green Artificial Intelligence regulations
20	Anand et al., 2024	No mention found
21	Clemm et al., 2024	European Union ecodesign directive, European Committee for Standardization-European Committee for Electrotechnical Standardization, self-regulation
22	Tabbakh et al., 2024	Need for policy proposals, tax incentives
23	Weng, 2025	"Peak carbon" targets, need for environmental, social, and governance disclosure
24	Masciari et al., 2025b	Green Software Foundation, energy efficiency targets
25	Bolón-Canedo et al., 2024	European Union Artificial Intelligence Act, strong European Union framework
26	Forgeval et al., "Carbon Footprint of Artificial Intelligence Data Centers"	Net Zero Scenario, increasing European Union constraints
27	Chaudhary et al., 2025	European Union guidelines, Artificial Intelligence Act, Assessment List for Trustworthy Artificial Intelligence
28	Alswaitti et al., 2024	Need for collaborative efforts, no specific
29	Marini et al., 2024	No mention found
30	Cruz et al., 2025	European Union Artificial Intelligence Act, need for key performance indicators/methodologies
31	Martin & Sharma, 2025	Lack of Artificial Intelligence governance
32	Raman et al., 2024	Need for robust frameworks, United Nations Sustainable Development Goals
33	Dash, 2025	No mention found
34	Liu, 2025	United Nations Educational, Scientific and Cultural Organization Education for Sustainable Development framework, ethical needs
35	Sowrirajan et al., 2025	No mention found

To sum up, key findings regarding the regulatory landscape from the above analysis show that many studies addressed more than one aspect. Specific regulations, laws or

frameworks, e.g. European Union Artificial Intelligence Act, General Data Protection Regulation, Health Insurance Portability and Accountability Act, United States Food and Drug Administration, California Consumer Privacy Act, European Union Ecodesign directive, Green Software Foundation, were mentioned in 12 studies. International Organizations or declarations e.g. World Health Organization, International Telecommunication Union, United Nations Sustainable Development Goals, United Nations Educational, Scientific and Cultural Organization, Organization for Economic Cooperation and Development, Institute of Electrical and Electronics Engineers, United Nations Framework Convention on Climate Change are reported in 8 studies. The most reported issue referred to Policy gaps, need for frameworks and lack of regulations which is reported in 14 studies. It highly mentioned the need for standardization, reporting or methodologies to act more environmentally friendly. The need for standardized reporting, energy reporting, key performance indicators and stricter standards reported in 10 studies. Aspects like tax incentives, carbon taxes, “peak carbon” targets, energy efficiency targets, Net Zero Scenario are mentioned in 6 studies. Two more studies emphasize collaborative efforts or public-private partnerships. I didn’t find any mention to the regulatory landscape in 8 studies.

4.1.3 Policy Gaps and Opportunities

Regarding the above analysis, the distribution of factors influencing sustainable Artificial Intelligence is broken down into three central pillars, as shown in table 12, which interact to determine the success or failure of green initiatives. The first component represents the organization itself; the structure of that organization is influenced by not only an organization’s internal structure and organization of function (i.e. Leadership) but also how that organization develops its corporate culture. The second component focuses on what types of technology are used (classifications) for example, whether the infrastructure is made up of physical assets (like computers/hardware) or whether the algorithms used are developed with the consideration of "How much energy is consumed?". The third component involves the pressure applied by regulatory authorities on the global level through their commitment to an organization (for instance, through their commitment to the United Nations) and how compliance with those global obligations applies and will

affect all three components of sustainable Artificial Intelligence.

The European Union's AI Act is the leading legislation for the European Union regarding Artificial Intelligence; however, many challenges lie ahead of its full implementation. **Compliance** constitutes a major challenge, as Member States are required to implement energy consumption and sustainability reporting obligations for AI systems. Existing research highlights that there is currently no unified approach to measuring or reporting the energy footprint of AI systems, resulting in fragmented compliance practices across jurisdictions (Verdecchia et al., 2023; Raman et al., 2024). Differences in national regulatory frameworks and institutional capacities are therefore expected to lead to divergent implementation outcomes among Member States (Haq et al., 2025; Azhar et al., 2025). Regarding **Best Practices**, the development of non-binding governance instruments such as Codes of Conduct, Regulatory Sandboxes, and mandatory reporting mechanisms for high-impact AI models is increasingly recognized as necessary to support innovation while ensuring sustainability and accountability. The literature emphasizes that regulatory experimentation and practical guidance mechanisms are essential to operationalize policy objectives and facilitate real-world adoption of sustainable AI practices (Raman et al., 2024; Weng, 2025). It can be difficult to determine how much energy different AIs consume because there is no standardization in terms of young KPIs (Key Performance Indicators) or how these are measured across all industry sectors and during all stages of the AI lifecycle. Therefore, without these "common metrics and benchmarks", we have a limited ability to monitor, compare, and enforce the required levels of sustainable practices (Verdecchia et al., 2023; Raman et al., 2024). Although the EU's Artificial Intelligence regulatory framework is regarded as one of the most exhaustive frameworks in the world, the Enforcement Gap is still an area where the EU faces great challenges. Empirical evidence has pointed out that the lack of effective and specific instruments, as well as the lack of specific reporting and operating requirements, hinder the efficiency and positive impact of a sustainability-focused Artificial Intelligence regulatory framework (Haq et al., 2025; Azhar et al., 2025; Verdecchia et al., 2023). In this context, the development of harmonized technical standards and practical implementation guidelines emerges as a critical prerequisite for bridging the gap between legislative intent and the operational realities of

implementing the AI Act, particularly with respect to energy efficiency, sustainability reporting, and enforcement consistency across the European Union.

Table 12: Factors Influencing Green AI Adoption and Policy Implications

Factor	Type Dimension	Key Findings	Policy Implications
Drivers	Organizational	Leadership, culture, collaboration	Incentivize leadership, cross-sectoral partnerships
Drivers	Technological	Energy-efficient algorithms/hardware	Fund research and development, standardize efficiency metrics
Drivers	Environmental	Regulatory pressure, United Nations Sustainable Development Goals	Align policies with United Nations Sustainable Development Goals, enforce reporting
Barriers	Organizational	Resource/expertise gaps, resistance	Support training, provide incentives, address resistance
Barriers	Technological	Infrastructure, complexity, metrics	Invest in infrastructure, develop standards
Barriers	Environmental	Assessment challenges, embodied emissions	Mandate life cycle assessment, broaden scope beyond operational emissions
Regulatory	All	European Union leads, but gaps in standardization/enforcement	Harmonize standards, develop practical guidelines, monitor compliance

4.1.4 Summary of SLR findings

The adoption of Green Artificial Intelligence is shaped by a complex set of drivers and barriers across organizational, technological, and environmental dimensions, with regulatory frameworks—particularly within the European Union—playing a central

and cross-cutting role. The reviewed literature consistently emphasizes that regulatory pressure, sustainability objectives, and emerging governance mechanisms significantly influence both the pace and direction of Green AI adoption (Raman et al., 2024; Verdecchia et al., 2023).

Organizational Enablers are largely recognized as essential for effective Green AI adoption. Leadership engagement and commitment to sustainability through the organizational culture of the business are largely recognized as enablers for the successful execution of Green AI. Evidence suggests that organizations that are highly committed to sustainability and have strong leadership are well-equipped to adapt energy-efficient AI methodologies in their operations (Haq et al., 2025; Azhar et al., 2025). From a **technological perspective**, key drivers include advances in algorithmic efficiency, improvements in hardware and computational infrastructure, and a growing emphasis on reducing the energy intensity of AI systems. Several studies underline that innovations in model optimization and energy-aware system design are essential for mitigating the environmental footprint of AI across its lifecycle (Verdecchia et al., 2023; Raman et al., 2024).

Factors like **environmental** influences and governmental influences play a crucial role. The governmental factor of being forced by regulations, more in the context of the European Union, and the general aim of achieving sustainability objectives like aligning with the Sustainable Development Goals (SDG) of the United Nations appear to be the reasons for adopting Green AI. However, from the literature studies, it could be seen that there exist imbalanced implementations of sustainability regulations and energy efficiencies (Azhar et al., 2025; Haq et al., 2025). The literature also points to the necessity of overcoming obstacles to the implementation of Green AI (GAI)-related practices by identifying what barriers are frequently identified by the participating organizations involved with GAI project development (Verdecchia et al., 2023; Raman et al., 2024; Haq et al., 2025). Some of these barriers are commonly cited as a lack of financial resources, a lack of personnel with expertise or experience in AI development, a lack of collaboration amongst various stakeholders, challenges associated with the use of AI, a lack of appropriate infrastructure to support GAI development and implementation, and a lack of accepted methods of measuring or quantifying energy consumption and environmental impacts associated with AI use

(Verdecchia et al., 2023; Raman et al., 2024; Haq et al., 2025). Other identified barriers to GAI implementation are regulatory gaps and/or enforcement gaps, which can create uncertainty regarding compliance with regulations, resulting in less incentive for compliance (Verdecchia et al., 2023; Raman et al., 2024; Haq et al., 2025). Relative to the regulatory environment, the EU is generally viewed to be leading the way in developing regulations governing the use of AI. However, literature generally identifies problems with regulatory harmonization, cross-sectoral applicability (i.e., different industries), and the ability to transform high-level legislative objectives into enforceable tools and measurable objectives (Verdecchia et al., 2023; Azhar et al., 2023). The evidence supporting the various sectors, as well as the geographic regions they were collected from, is documented by a diverse set of studies, both in terms of analytical depth and empirical focus. Some studies analyze sector-specific information and others use broader conceptual or review-based analyses to show that there is a need for additional **empirical research** to underpin the development of evidence-based public policy based on the recommendations made (Raman et al 2024). From the above findings, it can be concluded that while Green Artificial Intelligence will have an impact on the future of the European Union, it will necessitate the coordinated actions of business leaders, technologists, and representatives of the relevant regulatory agencies. Many of the articles reviewed as part of this review indicate that to effectively convert the ambitious goals for sustainability into effective, real-world performance, the harmonization of standards, the establishment of open and transparent reporting, and increased collaboration between all sectors are critical (Verdecchia et al 2023, Haq et al 2025, Azhar et al 2025).

SLR analyzed 35 scientific studies covering technological, organizational, and institutional dimensions of Green AI. Concerning the **Technological Dimension**, the literature shows a high degree of technical maturity, with extensive use of energy consumption and carbon footprint measurement tools (e.g., CodeCarbon, CarbonTracker), as well as optimization techniques (pruning, quantization, energy-aware models). Many studies adopt a Green-by-Design approach, emphasizing the reduction of the environmental footprint of the IT systems themselves. At the **organizational level**, critical adoption factors emerge leadership commitment, integration of sustainability into strategy, availability of skills and resources. However,

the literature also mentions that there have been numerous barriers, like change resistance, knowledge barriers, and unclear economic value of investments pertaining to Green AI. Regarding the Environmental and Institutional Dimension, the factors of regulatory pressure and support for sustainable goals (SDG/ESG) seem to be influential in triggering adoption as well. Yet policy ambiguity and a lack of effective implementation facilitation in an organizational context stand out as mentioned factors.

4.2 Analysis and Findings of the regulatory framework

The Concept of Green Artificial Intelligence was for the most part a reaction to the rapidly increasing computational needs related to training and running these huge AI models, such as foundation models and LLMs, Schwartz et al. (2019) coined the term "Green AI" and contrasted it with "Red AI", which only optimizes for accuracy without considering resource consumption, whereas Green AI also aims to attain resource-efficient performance. The political basis for Green AI lies in its alignment with the goals of the European Green Deal and the wider digital transition.

The analysis consisted of a qualitative examination of European Union and international policy and regulatory documents related to Green AI. This stage sought to determine how principles of AI governance, sustainability, and ethical responsibility are represented within these policy frameworks. All selected documents, e.g., *EU Artificial Intelligence Act*, *European Green Deal*, *Digital Europe Programme*, *OECD AI Principles*, *UNESCO Recommendation on AI Ethics*, were reviewed systematically.

A qualitative **documentary analysis** was conducted to examine policy and regulatory documents that influence AI and sustainability governance. From the following list of regulations, we selected to analyze the most representative regulations.

Table 13: Regional Policy and Regulatory Frameworks Relevant to Green AI

Region	Policy/Regulation	Relevance to Green AI	Description / Contribution
Greece	Law 5164/2024 (CSRD transposition)	Indirect	Implements EU CSRD; companies must disclose ESG data, including CO ₂ from digital and AI operations.

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Greece	National Energy & Climate Plan (NECP 2024)	Direct	Includes goals for low-emission digital transformation; AI energy use is part of efficiency metrics.
Greece	National AI Strategy (2025)	Direct	Focuses on responsible and sustainable AI (Green & Ethical AI) using efficient models and renewable energy.
EU	AI Act (Regulation (EU) 2024/1689)	Direct	Sets governance for trustworthy and sustainable AI — promotes transparency and efficient resource use.
EU	Energy Efficiency Directive (EED) (Directive (EU) 2023/1791)	Direct	Requires improved energy efficiency for data centres powering AI workloads.
EU	Commission Delegated Regulation (EU) 2024/1364 (DC KPIs)	Direct	Mandates reporting of energy and cooling KPIs for data centres — key for AI sustainability tracking.
EU	Ecodesign Regulation (EU) 2019/424	Indirect	Sets energy performance standards for servers/storage used in AI computing.
EU	Ecodesign for Sustainable Products Regulation (ESPR) (EU) 2024/1781	Direct	Establishes eco-design and recyclability rules for IT and AI hardware.
EU	Corporate Sustainability Reporting Directive (CSRD) & ESRS	Indirect	Requires disclosure of environmental data including AI/cloud energy consumption.
EU	EU Taxonomy (Reg. 2020/852) – Activity 8.1	Direct	Defines sustainable criteria for green data centres and AI infrastructure investments.
EU	EU Green Public Procurement (GPP, 2020)	Direct	Encourages green criteria for cloud and AI-related IT procurement.
EU	Renewable Energy Directive (RED III) (EU) 2023/2413	Indirect	Promotes renewable energy use in AI-related data infrastructures.
EU	GDPR (Regulation (EU) 2016/679)	Indirect	Supports responsible AI by enforcing transparency and lawful data use.
EU	Data Act (Regulation (EU) 2023/2854)	Indirect	Enables efficient and fair data reuse — reduces duplication and energy overhead in AI.
Global	Germany – Energy Efficiency Act (EnEfG, 2023)	Direct	Obliges energy management and transparency for AI-hosting data centres.
Global	Singapore – Green Data Centre Roadmap (2024)	Direct	Focuses on renewable-powered and AI-optimized energy-efficient data centres.
Global	Netherlands – Local moratoria & zoning for hyperscale DCs	Indirect	Limits large AI compute hubs due to high environmental impact.
Global	France – Energy Code amendments (heat-recovery obligation)	Indirect	Requires waste heat reuse from data centres, including AI facilities.

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Global	China – Green/Low-carbon Data Centre Policy (various)	Direct	National policies promoting green energy and low-carbon AI infrastructure.
Global	India – National Data Centre Policy (2020+)	Indirect	Promotes sustainable digital infrastructure, including AI data centres.
Global	USA – ENERGY STAR (servers, storage, DC equipment)	Direct	Defines energy efficiency standards for AI hardware components.
Global	ISO/IEC 30134-2 (PUE) & 30134-9 (WUE)	Direct	Global standards for measuring energy and water efficiency in AI data centres.
Global	ITU-T L.1300 – Best practices for green DCs	Direct	Provides technical guidelines for designing and running energy-efficient AI infrastructure.
Global	OECD AI Principles	Direct	Promotes responsible, transparent, and sustainable AI aligned with environmental goals.
Global	Climate-Neutral Data Centre Pact (CNDP)	Direct	Voluntary industry pledge for carbon-neutral data centres by 2030 — core for Green AI.
Global	Green Software Foundation – Software Carbon Intensity (SCI)	Direct	Defines metrics to measure and reduce carbon emissions from AI software operations.

The AI Act as the Central Regulatory Pillar: The EU's AI Act (Regulation (EU) 2024/1689) represents the European Union's effort to regulate artificial intelligence. The AI Act categorizes each AI system into the following classifications of risk: unacceptable, high, limited and minimal. Each risk level has corresponding regulations. Most of the focus behind this regulation is on items related to fundamental human rights, safety and AI governance, however, there are also provisions in this regulation that pertain specifically to Green AI. One of those provisions mandates that the providers of general-purpose AI, including large foundation models, maintain records of the energy consumed while training the model. Energy consumption may be recorded either through direct measurement or reliable estimation from available computational resources. New to the Regulation is a general-purpose AI designated as posing systemic risk and therefore having increased regulatory obligations. People are starting to see that these huge AI models use so much power that it could be a risk. That said, some think the AI Act doesn't go far enough on the environment. Right now, it mostly says companies need to be open about energy use, but it doesn't force them to cut energy use or limit carbon emissions from their AI models.

Data Governance: GDPR, Data Act, Data Governance Act: Effective data management is a critical determinant of the environmental performance of AI systems (Verdecchia et al., 2023;

Schwartz et al., 2020). There are three big EU laws that set the rules: the General Data Protection Regulation (GDPR) (GDPR – Regulation (EU) 2016/679), the Data Act Regulation (EU) 2023/2854, and the Data Governance Act. The GDPR's rules, like using only the necessary data, being clear about why you're using it, and building privacy into everything from the start, push people to use less data and cut down on processing stuff that's not needed, which can lower energy use. The Data Act regulates the framework for accessing and using data generated by interconnected devices and Internet of Things (IoT) equipment, in line with the governance standards of Regulation (EU) 2022/868. It helps AI apps make better use of energy and resources, like with smart grids or making industries more efficient. The Data Governance Act makes it simpler to reuse public data that's protected and introduces ways to share data for social good. This means better access to good data for keeping an eye on the environment and doing AI research related to climate. Even though none of these laws are directly about being green, they really help Green AI goals in various ways.

Infrastructure and Data Centres: Energy Efficiency Directive & Delegated Regulation 2024/1364: The EU is strengthening the sustainability of Artificial Intelligence through strict supervision of its infrastructure. In this context, the revised EED Directive (2023/1791) introduces mandatory reporting of energy and water efficiency data from data centers at the EU level. Data centers are now required to disclose critical metrics such as Power Usage Effectiveness (PUE), Water Usage Effectiveness (WUE), the percentage of renewable energy used, and heat recovery and reuse levels. Commission Delegated Regulation (EU) 2024/1364 gets even more detailed, like which data centers must report (over 500 kW IT load), what numbers to report, how to format reports, and how often they submit them. This initiative lays the groundwork for a unified system for evaluating data centers in the EU, which may be linked to energy labels or mandatory performance standards. Given that data centers are the backbone of AI development and operation, these regulations are an indirect but highly effective mechanism for enhancing the sustainability of AI systems (Commission Delegated Regulation (EU) 2024/1364). (OK)

Ecodesign, Circularity, Corporate Sustainability & Sustainable Finance: Green AI is closely connected with ecodesign and circular economy principles. Commission

Regulation (EU) 2019/424 Ecodesign - Lot 9 established the minimum energy efficiency standards for servers and data storage devices, affecting the energy use of AI infrastructures. Regulation (EU) 2024/1781 Ecodesign for Sustainable Products (ESPR) can provide a new comprehensive framework to underpin environmentally sustainable product requirements, including Digital Product Passports covering energy performance, reparability, durability, and recyclability of ICT equipment. Directive 2022/2464 (CSRD) and the ESRS introduce a requirement for companies to report on emissions of Scopes 1 to 3, energy use, and climate transition plans in a way that will cover AI activities and data centers for the first time in main sustainability reports. Regulation (EU) 2020/852, or EU Taxonomy, outlines under what conditions data processing and hosting activities may be considered environmentally sustainable, using technical screening criteria such as energy efficiency, PUE, water efficiency, and renewable energy. Taken together, the measures more deeply embed sustainability into corporate governance, investment decisions, and lifecycle management of digital products.

Greece's National Framework and International Developments: Greece is gradually implementing the EU regulatory framework into national legislation. Law 5164/2024 adopts the CSRD and introduces the obligation for sustainability reporting by specific businesses, including companies providing data centers or deploying substantial AI infrastructures (Logos Law Firm, 2024; Ecovis, 2025). Law 5164/2024 (CSRD transposition) establishes Greece's first comprehensive ESG disclosure framework, ensuring consistency with EU sustainability standards. Companies operating in Greece must now prepare for structured data collection, materiality assessment, and ESRS-aligned reporting, with the first disclosures due in 2025 (Kyriakou Law Firm, n.d.). The updated NECP 2024 provides long-term energy and climate targets, aligned with EU policy, applicable to national digital infrastructure planning. At the same time, the National AI Strategy underlines responsible, human-centered, and sustainable AI development, along the lines of EU legislation. Internationally, Germany's Energy Efficiency Act provides ambitious requirements for data centers on minimum heat recovery and renewable energy supply. Singapore's Green Data Centre Roadmap requires PUE targets ≤ 1.3 for new capacity allocation. Industry-led initiatives include the Climate Neutral Data Centre Pact, which commits operators to PUE 1.3–1.4 and

100% renewable electricity by 2030 (Mayer Brown, 2024). These various international efforts illustrate the consensus building across major world economies to regulate the environmental footprint of digital infrastructures underpinning AI.

Findings were synthesized into a comparative framework summarizing regulatory coverage across different Green AI practices, e.g., model training efficiency, data-center sustainability, and hardware circularity. The analysis ultimately informed policy recommendations aimed at integrating environmental accountability into AI governance, including the development of standardized Green AI indicators, lifecycle reporting requirements, and stronger coordination between existing EU instruments.

Table: 14 Summary of Regulatory Coverage of Green AI Practice

Green AI Practice	Regulatory Coverage	Assessment
Measurement of energy and emissions during AI training	Partially covered (AI Act, CSRD)	Insufficient regulation
Data center sustainability	Covered (EED, CSRD)	Relatively mature framework
Energy-efficient hardware	Partially covered (ESPR, CSDDD)	Needs clearer provisions
Lifecycle and supply-chain circularity	Covered (CSRD, ESPR)	Adequate but fragmented
Software/runtime efficiency	Minimally covered	Significant regulatory gap

4.2.1 Gaps, Challenges, and Future Directions of the regulatory framework

Despite the EU's sophisticated regulatory architecture, there are several gaps and challenges that remain as shown in table 15.

First, the environmental provisions in the AI Act center around transparency and documentation without setting mandatory thresholds regarding energy consumption or emissions per model training cycle. Second, although the EU regulates data center

performance and product-level sustainability, it has not yet comprehensively addressed the full lifecycle of ICT hardware, including mining, manufacturing, supply chain emissions, and electronic waste. Third, energy consumption during the inference phase of AI models-especially at scale-is not captured systematically in reporting obligations. Fourth, international regulatory asymmetries may lead to "carbon leakage" if energy-intensive computing operations relocate to regulatory environments with weaker environmental standards (Henderson et al., 2020; Desislavov et al., 2023; Caravaca et al., 2025). Academic literature on Green AI underlines the importance of standardized methodologies for measuring carbon footprint per training and per inference, as well as the potential introduction of minimum efficiency standards for highly resource-intensive models (Rojahn & Grum, 2025; Kim, Yoo & Chung, 2025). According to the OECD (2022), the regulatory landscape will likely develop further toward more explicit sustainability obligations for AI systems in the coming years.

Table 15: EU's sophisticated regulatory architecture, obligations, gaps, limitations

Regulatory Instrument	Primary Objective	Green Obligations / Provisions	Impact on Green AI	Gaps / Limitations
AI Act (Reg. 2024/1689)	Risk-based regulation of AI systems	Energy consumption reporting for GPAI; documentation of compute; systemic-risk GPAI concept	Promote transparency and governance regarding resource-intensive models	No mandatory reduction targets; transparency-only approach
Energy Efficiency Directive (Dir. 2023/1791 – EED)	Union-wide energy efficiency	Mandatory reporting of PUE, WUE, renewable share, heat reuse for data centres	Regulates infrastructure hosting AI workloads	No binding thresholds for PUE/WUE
Delegated Regulation (EU) 2024/1364	Implementation of EED for data centres	KPIs, reporting formats, ≥500 kW thresholds; basis for EU rating scheme	Creates harmonised system for monitoring	No mandatory rating or sanctions yet

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			environmental performance	
Ecodesign (Reg. 2019/424 – Lot 9)	Energy performance of ICT hardware	Minimum efficiency requirements for servers and storage	Improves energy sustainability of AI infrastructure	Limited scope; does not cover full hardware lifecycle
ESPR (Reg. 2024/1781)	Sustainable product design framework	Digital Product Passports; durability, repairability, recyclability for ICT	Promotes circularity and transparency in AI hardware	Requires product-specific delegated acts
CSRD (Dir. 2022/2464)	Mandatory sustainability reporting	Reporting of Scope 1–3 emissions, energy use, and data centre impacts	Integrates AI footprint into corporate governance	Lacks AI-specific reporting categories
ESRS (Del. Reg. 2023/2772)	Harmonised ESG standards	Detailed reporting on emissions and energy use	Increases transparency for firms deploying AI	No AI-specific KPIs yet
EU Taxonomy (Reg. 2020/852)	Criteria for sustainable investments	Technical criteria for data hosting (PUE, renewables, water efficiency)	Defines when AI-related investments qualify as green	Limited to select economic activities
GDPR (Reg. 2016/679)	Data protection	Data minimisation; privacy-by-design	Indirect reduction of data-processing overhead	Not designed for sustainability goals
Data Act (Reg. 2023/2854)	Fair access to IoT and other data	Enables energy/resource optimisation via AI	Supports green-by-data innovation	Not an environmental instrument per se
Data Governance Act (Reg. 2022/868)	Re-use of protected public data; data altruism	Facilitates access to environmental datasets	Supports climate-related AI research	Limited enforcement mechanisms
NECP & National AI Strategy (Greece)	Alignment with EU climate and digital goals	Energy efficiency targets;	Provides national-level guidance	High-level, non-binding technical requirements

		sustainable AI references		
International frameworks (Germany, Singapore, CNDCP)	Regulation of digital infrastructure	Heat reuse mandates; strict PUE; 100% renewables (industry pact)	Set global benchmarks for sustainable AI infrastructure	Regulatory divergence risks carbon leakage

The EU has developed the world's most advanced regulatory landscape for sustainable AI, however, explicit rules that directly target Green AI, i.e., model-level energy and carbon performance across the AI lifecycle, remain comparatively limited in the academic and policy discourse, with several reviews noting that green AI governance and systematic operationalization are still emerging (Tabbakh et al., 2024; Alzoubi & Mishra, 2024). Binding obligations stem mostly from the Energy Efficiency Directive and Delegated Regulation 2024/1364 (Directive (EU) 2023/1791; Commission Delegated Regulation (EU) 2024/1364), while the AI Act focuses on transparency provisions without laying down any requirements in the fields of GHG emissions or energy reductions (Regulation (EU) 2024/1689). Most existing legislation targets data center infrastructure rather than the AI models themselves, meaning most lifecycle emissions and inference-related energy consumption fall outside the scope of regulation (Tabbakh et al., 2024; Verdecchia et al., 2023). Sustainability concerns are nonetheless being gradually integrated into hardware lifecycle governance by means of instruments like the ESPR and Ecodesign frameworks-a step in the right direction since there is close interlinkage between the development of AI models and computing hardware (Regulation (EU) 2024/1781; Directive 2009/125/EC; International Energy Agency, 2024). Corporate sustainability regimes, such as the CSRD, ESRS and EU Taxonomy, also constitute effective indirect mechanisms of regulation insofar as they require businesses to disclose the environmental footprint of their digital operations, including energy use and climate-related impacts, even when AI-specific mandates are lacking (Directive (EU) 2022/2464; Commission Delegated Regulation (EU) 2023/2772; Regulation (EU) 2020/852). Standardized approaches for the estimation of the carbon footprint of AI training and inference, which is the subject of broad consensus in both academic and policy debates-are expected to be followed by future regulatory developments, introducing explicit

environmental performance criteria for AI systems (Henderson et al., 2020; Verdecchia et al., 2023; Desislavov et al., 2023).

The analysis of the European institutional framework focused on key regulatory and strategic tools of the European Union related to Artificial Intelligence, sustainable development, and the green digital transition, such as the Artificial Intelligence Act (AI Act), the European Green Deal, and relevant eco-design and sustainable corporate governance directives.

The results of the analysis show that the environmental dimension of Artificial Intelligence is recognized at a strategic level, but its integration into the binding regulatory framework remains limited. Specifically, the sustainability of AI is viewed largely as a horizontal policy issue, not being coupled with technical requirements for AI systems. The AI Act is mainly oriented towards risk management, transparency, and the guarantee of basic rights, but it does not provide any specific indicators to measure energy or carbon footprints. Environmental legal requirements for digital technology seem fragmented in nature and lack binding relevance to the life cycle for AI.

The analysis revealed major institutional gaps that hinder the effective adoption of Green AI, such as, (1) the absence of mandatory measurement of energy consumption and CO₂ emissions for AI systems, (2) the lack of standardized Green AI indicators and (3) limited interoperability between digital policy and environmental governance.

Overall, the institutional framework acts primarily as a **source of coercive pressure**, without providing sufficient operational guidance for the practical implementation of Green AI at the organizational level (Pasamar et al., 2024; Liang et al., 2023).

4.3 Comparative Synthesis of Institutional Framework and SLR findings

This chapter presents the results of the study that emerged from the combined analysis of the regulatory framework and the systematic literature review (SLR) on the adoption of Green Artificial Intelligence (Green AI). The aim of this chapter is to holistically synthesize the findings and conceptually integrate them into the theoretical frameworks of the research, leading to the design of the proposed Green AI Adoption Framework with the help of the integration of the findings of the empirical interviews.

A comparative examination of the results of the analysis of the regulatory framework and the findings of the Systematic Literature Review (SLR) reveals both significant convergences and substantial divergences in the adoption of Green AI. In terms of convergence, both the European institutional framework and the scientific literature recognize that Artificial Intelligence is a critical lever for the digital transition, with a parallel increase in its environmental footprint. European Union strategies, such as the European Green Deal and ESG frameworks, place sustainability as a horizontal policy priority, while the literature shows extensive convergence on the need to reduce energy consumption and CO₂ emissions at all stages of the AI systems' life cycle. However, there is a clear asymmetry between regulatory ambition and operational feasibility. Institutional analysis shows that the AI Act and related regulatory tools focus primarily on risk management and transparency, without incorporating binding and measurable energy efficiency or carbon footprint indicators. In contrast, SLR highlights mature technical tools, such as CodeCarbon and CarbonTracker, which allow the environmental impact of AI to be quantified but remain outside the binding regulatory framework. The comparison shows that the main gap is not the lack of technological solutions, but their non-institutional integration. Literature operates mainly through regulatory and imitative pressures, while the institutional framework is based mainly on coercive mechanisms. This asymmetry demonstrates the need for an intermediate, organizationally applicable framework that bridges strategic policy direction with practical implementation. This need led to the development of the Green AI Adoption Framework, which synthesizes the institutional requirements with the technical and organizational findings of the literature.

Comparative analysis reveals a clear **asymmetry** between the institutional framework and scientific knowledge. While EU policy is characterized by strategic ambition, the literature offers mature, measurable, and technically feasible solutions that have not yet been systematically incorporated into the regulatory framework.

Literature operates mainly through **normative** and **mimetic** institutional pressures, in contrast to the institutional framework, which is based on coercive regulation. Below you will find the above results presented in table 16.

Table 16: Green AI Practices and Regulatory Alignment

Green AI practice ↓ / Regulation →	AI Act	CSRD	CSDDD	ESPR	Energy Efficiency Directive / Data-centre KPIs	EU Taxonomy / Energy Policy	Green Public Procurement / Guidance	Coordinated Plan on AI / Digital Strategies
1. Model training energy & carbon measurement (per-model)	Partially covered — Transparency obligations (esp. for GPAI); delegated acts expected to set metrics. Partially covered — AI Act may require provider disclosures but not data-centre KPI regime directly.	Partially covered — Forces org-level emissions disclosure; pushes measurement but not per-model standards. Covered (indirectly) CSRD will capture provider emissions; data-centre KPIs become reportable inputs.	Partially covered — May require identifying environmental impacts in supply chain (can include compute). Partially covered — May require attention to data-centre supplier impacts.	Under-regulated — Focus is hardware/product; software/model-level measurement not explicit.	Under-regulated — Focuses on data-centre KPIs, not per-model training metrics. Covered — Delegated rules and recast EED create EU KPI reporting and sustainability rating for data centres.	Under-regulated — Encourages green investments but does not define per-model metrics.	Under-regulated — Procurement guidance may request sustainability but lacks model-level measurement rules.	Under-regulated — Encourages R&D and best practices but no binding model-level metrics yet.
2. Data-centre sustainability reporting (PUE, energy source, KPIs)				Partially covered — Applies mainly to products/hardware, so indirect for data-centre hardware.		Partially covered — Influences investment to green data centres (indirect).	Partially covered — Procurement can require data-centre sustainability evidence.	Partially covered — Encourages digital infrastructure sustainability and coordination.
3. Energy-efficient hardware	Under-regulated — AI Act not focused on	Under-regulated — CSRD captures impacts but	Under-regulated — Doesn't set product specs;	Partially covered — Targets product/ecodesign; hardware	Partially covered — Affects operational	Partially covered — Can classify green	Under-regulated — Procurement can prefer	Under-regulated — No binding hardware

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(servers, chips) & ecodesign	hardware ecodesign.	does not set hardware performance requirements.	may affect supplier choices.	improvements in scope though software gaps remain.	efficiency; not direct product-spec regulation.	hardware investments.	green hardware but lacks uniform mandatory specs.	ecodesign rules yet.
4. Lifecycle & supply-chain carbon / circularity for AI products	Partially covered — AI Act encourages transparency and risk management, but lifecycle specifics limited. Under-regulated — Not a central focus; transparency obligations may encourage reporting.	Covered — Requires lifecycle/scope disclosures for large companies; strongly relevant to AI supply chains. Under-regulated — May indirectly incentivize efficiency by reporting emissions.	Covered (operationally) — Requires companies to mitigate adverse environmental impacts along value chains. Under-regulated — May trigger efficiency actions if material.	Partially covered — Addresses product circularity (hardware), less so software lifecycle. Under-regulated — Focuses on products; software efficiency coverage is weak.	Under-regulated — Addresses operational efficiency, not full lifecycle circularity. Under-regulated — Doesn't measure individual software efficiency.	Partially covered — Influences investments with lifecycle criteria for certain activities. Under-regulated — Not specific to runtime software efficiency.	Partially covered — Can integrate lifecycle criteria; practice varies by buyer. Under-regulated — Procurement rarely enforces software-efficiency KPIs yet.	Partially covered — Encourages lifecycle thinking; no binding lifecycle rules specific to AI.
5. Runtime / inference efficiency (software-level best practices)	Partially covered — Delegated acts and standardisation under AI Act may create benchmarks.	Under-regulated — Requires disclosures but not standardised model benchmarks.	Under-regulated — Doesn't set technical benchmarks.	Under-regulated — Not focused on software/model benchmarks.	Under-regulated — Has data-centre metrics, but not model benchmark standards.	Under-regulated — Does not provide model efficiency benchmarks.	Under-regulated — Lacks standard model-efficiency scoring.	Partially covered — Promotes efficient AI use; standards still voluntary.
6. Standardised benchmarking for model efficiency (comparability)								Partially covered — Funds standardisation work; voluntary benchmarks exist.

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7. Procurement & contract clauses to require green AI	Partially covered — AI Act provisions affect public purchases indirectly; not uniform procurement mandates.	Partially covered — Makes emissions visible, enabling green procurement choices.	Partially covered — Informs procurement risk assessments.	Under-regulated — Affects product specs but not procurement clauses for AI services directly.	Partially covered — Data-centre KPIs can be required by procurers where relevant.	Partially covered — Helps buyers identify sustainable investments.	Partially covered / practical — Guidance exists; obligations vary by Member State. Under-regulated — Procurement can favor green investments but usually lacks direct financing instruments.	Partially covered — Promotes green public procurement; implementation varies.
8. Incentives / financing for low-carbon computers & renewables for AI	Under-regulated — AI Act is regulatory, not a financing instrument.	Under-regulated — Shapes investor behavior but not direct incentives.	Under-regulated — Not a financing tool.	Under-regulated — Not a financing instrument.	Partially covered — Indirectly shapes incentives for efficient operation.	Covered (indirectly) — Creates channels for green finance to low-carbon infrastructure.		Partially covered — Channels R&D and public funds toward green AI projects.

This assessment demonstrates that, as it stands now, a relatively low level of coverage exists in the European Union at this stage regarding different types of major regulatory and policy frameworks that have been developed by the European Commission and other EU member states. Furthermore, only a limited number of practices associated with the respective regulatory or policy frameworks have been systematically mapped out or documented over the years. For example, in the context of the Artificial Intelligence Act, it is particularly apparent because it includes both a general framework and separate regulatory requirements under the AI Regulation, along with the Corporate Sustainability Reporting Directive, Data Governance Act, and Data Act, among many others e.g., energy policy, EU Corporate Taxonomy, and GDPR (European Commission, 2021; European Parliament and Council of the European Union, 2016, 2022). The limited nature of this coverage suggests that urgent action is required to activate the workflows that will facilitate the integration of sustainability-related key performance indicators (KPIs) and mechanisms for controlling risks into both the organization's and the technology's processes. In terms of Artificial Intelligence, Europe's latest AI regulations mandate companies to maintain documentation related to their AI technology, implement risk management safeguards, and manage data appropriately. These regulations mandate having a defined structure in place to evaluate and hold corporations accountable throughout the entire life cycle of their AI systems (European Commission, 2021). The EU Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS) necessitate organizations to report on their most significant environmental and energy performance indicators, comprising their total energy consumption and greenhouse gas emissions, to illustrate how Corporate Governance of AI integrates with achieving the Sustainable Development Goals. The EU Taxonomy has been introduced as a means of categorizing 'green' (i.e. sustainable) business activity and will also contribute to measuring the Ecological Footprint of all digital and AI-based technology infrastructure. To ensure that AI systems adhere to regulatory requirements and provide organizations with an accurate means of demonstrating their compliance with the law, organizations must incorporate energy-related and carbon-related KPIs into their AI systems' documentation. They also need to expand the model card concept to include environmental-related metrics as part of their ML Offload Procedures, and to further strengthen the governance of ML Offload Procedures by requiring computational budget approvals, i.e., the funds needed to support the development and deployment of AI systems, and evidence of the proper use of a suggestion-based ML framework. This mapping will provide a useful framework for future evaluations of AI compliance with the EU Artificial Intelligence (AI) Act, GDPR, and the broader European data governance regime, as well as being valuable tools for providing a reliable and comprehensive measure of sustainability compliance that reflects the increasing expectations placed upon organizations by European policy and regulation (European Commission, 2022, 2023).

4.4 Analysis and Presentation of Empirical Findings (interviews)

Having selected the appropriate population for the research to conduct the interviews, the following interview protocol was drawn up. As mentioned above in the methodology chapter, the target population consisted of experts in the field of AI from academia and research, public sector organizations, and private companies which are developing AI systems. An Invitation was sent to 17 candidates for participating in the interviews by email, to which 13 responded positively. The questionnaire was distributed to each participant after consent to participate in the interview had been obtained (see Appendix). In the end, 11 of the 13 were able to participate. The other two were unable to participate due to increased professional commitment. Specifically, the distribution of participants in the interviews is as follows: Three researchers at the Institute of Informatics and Telecommunications and Institute of Nuclear & Radiological Sciences and Technology, Energy & Safety of NCSR, with purely research-based duties, working on projects and one of them is the head of the organization's Network Center. The director and president of the Board of the National Center for Scientific Research "Demokritos (NCSR) which is the largest interdisciplinary public research center in Greece. One participant comes from the academic sector, holding the position of Associate Professor, Department of Informatics and Telematics, at Harokopio University of Athens, Greece. Three experts, the company Director, an advisor of the e-Government Directorate on digital transformation issues and an external partner of GRNET S.A., which is a Greek public company and holds the key role as the coordinator of all matters regarding the provision and maintenance of national infrastructures for Education and Research, is the national representative for the research and technology community for European Union's infrastructures and manages the Government Research and Education Cloud (RE-Cloud). The General Director of the Open Technologies Organization ELLAK, a non-profit NGO with the aim of promoting open technologies, open data, open government, open infrastructure, and open standards. And finally, two experts of the private sector, developing AI applications and public projects, managing the entire AI, research & development department. The one of them refers to a non-profit technology organization that operates in the fields of innovation, artificial intelligence, and technology for social good, providing services to public bodies and training regarding AI issues.

The interview was conducted in Greek, while the questionnaire is included in the appendix in both languages (Greek and English). The interviews were conducted online due to time constraints and moving restrictions and were recorded using the Zoom platform. Interview transcriptions were produced using a customized version of the open-source Whisper speech recognition system developed by OpenAI. The interview protocol

gathered valuable information from the respondents, a summary of which and the main conclusions are presented below.

The empirical findings show that the adoption of Green AI is seen as a strategic necessity, but is characterized by high complexity and uncertainty, as has also been pointed out in international literature (Verdecchia et al., 2023; Haq et al., 2025). Participants acknowledged the importance of energy efficiency and environmental impact measurement but pointed out the lack of operational tools and incentives for implementation (Floridi & Cowls, 2021; Haq et al., 2025).

The empirical data analysis found that experts consider Green AI adoption as a strategic requirement, but express concerns about the complexity and uncertainty associated with the process. Experts agree that a strong focus on energy efficiency, environmental impact assessment and alignment with sustainability goals is necessary for effective implementation. The absence of operational tools and operational guidelines, coupled with the absence of incentives to implement Green AI, was noted by them. Most experts indicated that the effective implementation of the principles of Green AI will depend on the degree of leadership support, the culture within their organization and regulatory clarity.

Data from semi-structured interviews were analyzed using **thematic analysis** (Braun & Clarke, 2006). Key concepts were extracted and categorized under three overarching domains aligned with the Technology–Organization–Environment (TOE) framework, Innovation resistance Theory (IRT) and Institutional Theory (IT):

- **Technological dimension** – energy efficiency, algorithmic transparency, and digital innovation.
- **Organizational dimension** – governance mechanisms, capacity building, and ethical oversight.
- **Environmental/institutional dimension** – regulatory standards, societal expectations, and sustainability targets.

The process involved several iterative steps:

1. **Familiarization:** Transcripts were read repeatedly to identify initial impressions and emerging meanings.
2. **Coding:** A combination of **deductive coding** (based on TOE, IRT and IT frameworks) and **inductive coding** (emerging directly from participants' narratives) was applied.
3. **Theme Development:** Codes were clustered into themes reflecting common patterns such as *technological readiness, organizational learning, regulatory compliance, energy efficiency, and ethical accountability*.

Codes were developed inductively to capture emerging patterns and deductively to align with the predefined categories of TOE, IRT and IT. Below, in table 17 you can find the coding scheme for the Qualitative of Green AI Adoption.

Table 17: Coding Scheme for the Qualitative Analysis of Green AI Adoption

Theme	Codes
Level of AI Adoption	Existing AI use; Experimental AI use; Research-oriented AI use; Absence of organizational AI adoption
Familiarity with Green AI	Theoretical familiarity; Research-level familiarity; Organizational unawareness; Conceptual ambiguity
Adoption Drivers	Energy costs; Environmental awareness; European policies; Innovation; Digital sovereignty
Technical Barriers	Lack of high-quality data; Infrastructure complexity; Lack of appropriate tools; Lack of automation
Organizational Barriers	Absence of strategy; Resistance to change; Organizational culture; Slow decision-making processes
Skills-related Barriers	Lack of training; Need for upskilling; Uneven distribution of knowledge among staff
Value-related Barriers	High costs; Uncertainty of return on investment (ROI); Benefits not immediately observable
Adoption Risks	Reliability of outcomes; Inaccurate sustainability measurement; Regulatory ambiguity
Reputational and Image-related Barriers	Fear of underperformance; Public criticism; Reputational risk
Role of Policy	European-level directions; National policies; Institutional incentives
Success Factors	Education and training; Pilot projects; Demonstration use cases; Governmental support

The coding scheme was developed using a hybrid qualitative approach. The analytical themes were informed by the literature and the research framework, while the specific codes emerged inductively through iterative analysis of the interview data.

The coding framework is consistent with the Technology–Organization–Environment (TOE) model. The themes of Level of AI Adoption, Familiarity with Green AI, and Technical Barriers are more closely related to the Technology dimension. Then, there are themes such as Organizational Barriers, Skills-related Barriers, Value-related Barriers, and Success Factors that are more aligned with the Organizational dimension. Finally, there are themes such as Role of Policy, Adoption Risks, and Reputational and Image-related Barriers that are more aligned with the Environmental and Institutional dimension. This helped to ensure consistency in analysis between the findings, the theory, and the research question.

Recurrent themes were extracted, and suggested modifications were incorporated into the final version of the Green AI Adoption Framework. This process ensured that the framework reflected both **theoretical rigor** and **practical usability**.

The analysis of the interviews revealed that Green AI is not implemented based on an organized plan, but is adopted incidentally, mainly to save resources, comply with energy limits, or participate in European programs. The most important findings of the thematic analysis of the interviews concern issues like Conceptual Confusion, which means that the use of AI for environmental protection (AI4Green) is often confused with efforts to make AI itself less energy-intensive (Green AI). Also emerged long-term obstacles, such as progress is hampered by poor data quality, complex technical infrastructure, and a lack of standard procedures. Moreover, the human Factor plays a major role, because resistance to change and a lack of expertise are common problems in the public, private, and academic sectors. Finally, the Role of Policy is crucial given that European guidelines are the main driver for progress, as without them there is inertia. Refraining from Green AI practices is no longer considered a simple omission, but a serious threat to the future credibility and competitiveness of an organization in the market.

The results of qualitative research show that the adoption of Green Artificial Intelligence is at an early stage of maturity. Although the use of AI systems is widespread, the environmental dimension is not systematically integrated into their design and operation. The lack of a common understanding of the term "Green AI" leads to fragmented practices, which are often limited to cost reduction or energy efficiency of infrastructure, without a holistic approach. At the same time, the absence of sustainability measurement methodologies makes it difficult to document the benefits. Organizational and cultural barriers, combined with a lack of skills, emerge as critical obstacles, regardless of the organization's field of activity.

4.4.1 Analysis of Findings Based on Theoretical Dimensions

4.4.1.1 Technology / Organization Readiness for Green AI

The findings show that technological and organizational readiness for the adoption of Green Artificial Intelligence appears to be **uneven and fragmented**, with a clear distinction between research and organizational use.

At the **technological level**, most organizations have **basic AI infrastructure** (computing power, data centers, AI tools), but these have not been designed from the outset with energy efficiency or environmental sustainability criteria in mind. Green AI is mainly implemented indirectly, though, (1) the use of smaller models due to cost, (2) limitation of computing resources or (3) infrastructure optimization (e.g., consumption monitoring).

However, systematic practices such as automated energy optimization, standardized sustainability measurement methodologies, and integrated Green AI design frameworks are lacking.

At the **organizational level**, readiness is considered **lower**. Although expertise exists at the individual or research level, it rarely translates into a unified strategy, institutional decisions, or organizational policies for Green AI.

Several organizations are in a transitional stage where Green AI is recognized as a future necessity, but have not yet been integrated into the core of digital transformation. Overall, readiness is characterized as **partial, non-systematic, and dependent on individuals and projects** rather than organizational structures.

4.4.1.2 Types of Resistance / Perceived Barriers relating to Green AI

The analysis revealed a wide range of resistance and perceived barriers, which can be categorized as technical, organizational, cognitive, and value related. Technical barriers appear consistently in the interviews and mainly concern, (1) the lack of quality and appropriate data, (2) the complexity of data preparation, (3) the complexity of designing energy-efficient systems, and (4) the increased need for maintenance and monitoring.

At the same time, there is strong **organizational resistance**, which is not necessarily expressed as refusal, but as hesitation, delay, and lack of prioritization. Resistance is linked to established practices, workload, slow decision-making, and difficulty in changing culture.

Of particular importance is the **lack of skills and training**, both at the technical and administrative levels. Many participants point out that Green AI requires a new way of thinking, which has not yet taken root in organizations.

Finally, there are **barriers to perceiving value**, as the benefits of Green AI are not immediately measurable or visible. Uncertainty about the return on investment, combined with fears of reduced model performance, acts as a deterrent. In some cases, concerns about potential reliability and reputation risks are also mentioned, particularly in public service delivery environments.

4.4.1.3 Institutional and Policy Environment shaping Green AI implementation

The institutional and political environment emerges as a key external factor for the adoption of Green AI. The findings show that adoption is largely linked to European guidelines, funding projects, and regulatory developments.

European policies mainly act as an external accelerator, pushing organizations to consider sustainability practices that would not otherwise be a direct priority. At the same time, the absence of a clear and specific regulatory framework for the energy dimension of AI creates uncertainty and slows down implementation. The state appears in the findings more as a regulator and financier than as a strategic guide. Participants point to the need for clear incentives, the incorporation of sustainability criteria into calls for proposals, pilot projects and sandbox environments, and mechanisms for certifying or evaluating Green AI practices.

Finally, the institutional environment also influences risk perception as regulatory uncertainty and the lack of standards make organizations more cautious, especially regarding public accountability and credibility. Overall, the findings indicate that the adoption of Green AI is shaped by the **dynamic interaction** between (1) limited organizational readiness, (2) multilevel resistance, and (3) an institutional framework that acts more as external pressure than as internal motivation. Green AI is recognized as strategically important, but the transition from recognition to practice requires the simultaneous strengthening of all three dimensions.

4.4.1.4 Discussion of Findings in Connection with the Bibliography

This section discusses empirical findings considering the international literature on Green Artificial Intelligence, focusing on three analytical dimensions: technological/organizational readiness, resistance, and institutional environment.

(a) Technology/Organizational Readiness

The existing bodies of literature suggest that for Green AI to be realized, there needs to be adequate technical infrastructure and enough organizational capacity to ensure that sustainability is integrated across the entire AI lifecycle. Much of the previous research has focused on how the adoption of Green AI is a socio-technical process influenced by such things as governance structures, strategic alignment, and institutional commitment, as opposed to just energy-efficient computing resources (Schwartz et al., 2019; Verdecchia et al., 2023; Clemm et al., 2024). These findings support this distinction.

Although most organizations have developed AI infrastructures, readiness for Green AI remains partial and unsystematic. Sustainable development is typically both indirectly incorporated (e.g. via cost savings, or resource conservation) and as not obviously being part of a design purpose. This is in line with the literature that indicates that many organizations fail to separate infrastructure's energy efficiency from Green AI, which is a more inclusive approach (Strubell et al., 2019; Henderson et al., 2020; Verdecchia et al., 2023).

Also, there is a difference between how developed Green AI research is and the readiness of organizations to use Green AI, which means that it isn't enough for organizations to have knowledge about the environment and technical skills for them to be able to implement Green AI. By previous studies, Green AI can only be successfully implemented with the appropriate organizational governance processes, leadership commitment to the environmental objectives and strategic planning for implementation (Floridi & Cows, 2021; Eccles et al., 2014; Kotsantonis et al., 2016). Without these supporting structures, sustainability initiatives are disjointed and will not contribute to the consistent implementation of Green AI.

(b) Types of Resistance / Perceived Barriers

According to the literature on innovation diffusion, obstacles to adopting innovative technology can be categorized in three ways: utilizing technology (technical constraints), functioning with it (cognitive barriers), and having certain types of characteristics/values presents, cultural or value-based barriers. The elements of the Innovation Resistance Theory, specifically focused on the organizational resistance to technologies because of their level of risk, uncertainty, and alignment with the established organizational norms and practices (Ram & Sheth, 1989) and are reported in other innovative literature and recent research. Our research study findings confirm that barriers to Green AI adoption stem from many different sources. Technical barriers relating to access to data, complexity of the system or processes involved, and ongoing maintenance requirements correspond to the findings of various studies (Strubell et al., 2019; Henderson et al., 2020; Verdecchia et al., 2023) that identified similar energy optimization and lifecycle efficiency as particularly challenging technical challenges to implementing Green AI. Although the research findings do provide evidence that technical barriers exist, they primarily demonstrate that the largest barriers are not purely technical barriers, but rather organizational and cognitive barriers.

Organizations encounter passive barriers to their adoption of Green AI practices due to their resistance to change; the scarcity of talent with the requisite skill set; and the lack of an agreed-upon definition for what Green AI means. Prior studies indicate that a lack of support for a sustainability-oriented culture and misalignment within their internal structures are additional barriers to the institutionalization of these practices (Eccles et al., 2014; Kotsantonis et al., 2016; Haq et al., 2025). Uncertainty about the value proposition and return on investment of Green AI initiatives adds further support to the findings of previous work that suggest that organizations often treat sustainability objectives as an afterthought to performance or efficiency or as less important than immediate economic benefits (Schwartz et al., 2020; Floridi & Cowls, 2021; Verdecchia et al., 2023).

(c) Institutional and Policy Environment

International literature recognizes of how Institution Environment is one of the most powerful forces impacting on the rate of adoption of Sustainable Technologies indicate that the institutions can exert significant coercive, normative and mimetic influences (DiMaggio and Powell, 1983; Scott, 2014). The findings of the study show that in Greece, the use of Green AI has been heavily influenced by external Institutional factors, particularly EU policy and regulatory frameworks (European Commission, 2020; Floridi & Cowls, 2021).

Policymaking around sustainable development has been primarily about creating coercive compliance mechanisms. Organizations have not typically been incentivized to proactively incorporate the concepts of

sustainability into their business strategies, mainly due to lack of clarity on measuring and verifying sustainability performance (e.g., Jobin et al., 2019; Verdecchia et al., 2023). Furthermore, there is much regulatory uncertainty regarding how best to measure and report on sustainability, and how to certify/recognize an organization as being "Green," leading organizations to approach adopting Green AI with great caution (Henderson et al., 2020; Raman et al., 2024).

According to the literature, low-risk experimentation methods such as pilot projects, targeted incentives and regulatory sandboxes help address these barriers by allowing organizations' ability to test Green AI solutions without creating uncertainty or risk perception (Floridi et al., 2019; European Commission, 2021; Verdecchia et al., 2023). These mechanisms have also been found to act as valuable transitional instruments that allow for continued innovation while maintaining regulatory oversight and compliance with sustainability goals.

Below you can see an Explicit Mapping of Findings in the TOE Framework (table 18) and the next table 19 presents the main empirical findings mapped across three analytical dimensions (Readiness, Resistance, and Policy) as they described above and explicitly linked to the TOE framework (Technology, Organization, Environment) in the context of Green AI.

table 18: Green AI Adoption – Interview Findings in the TOE Framework

TOE Dimension	Subcategory	Interview Findings
Technology	Infrastructure	AI infrastructures exist, but they are not designed for Green AI
Technology	Data	Lack of high-quality data; high cost of data preparation
Technology	Complexity	Complex system design; increased maintenance requirements
Organization	Strategy	Absence of an organizational Green AI strategy
Organization	Culture	Resistance to change; hesitation toward adoption
Organization	Skills	Need for training and upskilling
Organization	Value Perception	Uncertainty about ROI; benefits not immediately visible
Environment	Policies	Strong influence of European policies

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Environment	Regulations	Regulatory ambiguity regarding AI sustainability
Environment	Funding	Projects and incentives as key driving forces
Environment	Institutional Pressure	Fear of credibility loss and public accountability

table 19: Table of Findings – three Dimensions

Main Finding	TOE Dimension	(a) Readiness	(b) Resistance	(c) Policy
Fragmented Green AI adoption	Technology / Organization	✓		
Lack of high-quality data	Technology	✓	✓	
Infrastructure complexity	Technology	✓	✓	
Skills shortage	Organization		✓	
Resistance to change	Organization		✓	
ROI uncertainty	Organization		✓	
European policies as a driver	Environment			✓
Regulatory ambiguity	Environment		✓	✓
Need for pilot projects	Technology / Organization / Environment	✓	✓	✓

The matrix illustrates that Green AI adoption is shaped by interdependencies across all TOE dimensions. Technological readiness has a large degree of correlation with readiness-related findings. Resistance to adopting technology has a strong correlation with organizational readiness and is then greatly impacted by organizational and environmental variables. Pilot programs offer a cross-cutting mechanism to concurrently improve technology readiness, reduce/resist adoption and alignment of organizational practices with policy objectives.

The comparative analysis of the eleven cases revealed strong recurring patterns, despite differences in the type of organization (public, research, academic, private, non-profit). Green Artificial Intelligence does not appear to be a fully institutionalized practice in any category of organizations, but as an **emerging and transitional field**, with varying degrees of maturity.

A common finding in all cases is the **asymmetrical development between technological capability and organizational readiness**. While technical knowledge and AI infrastructure are often adequate or even advanced, especially in research environments, the integration of the environmental dimension remains

fragmented and unsystematic. Green AI is not treated as an independent strategic choice, but mainly, as (1) a cost by-product, (2) as a project or policy requirement, or as (3) a limited research direction.

The analysis shows that the adoption of Green Artificial Intelligence is not a linear technological development, but the result of the interaction of technological capabilities, organizational dynamics, and institutional pressures. Strengthening only one dimension is not enough; coordinated intervention in all three is required.

4.5 Synthesis of results - Cross-Dimensional Synthesis of the results

A detailed assessment of the cross-analysis has confirmed an interrelationship among technological factors, organizational factors, institutional factors, etc., thereby supporting the potential of using multi-level analysis frameworks (Scott, 2014; Verdecchia et al., 2023).

This section of the chapter will summarize how empirical evidence from the research can provide insight into the broader theoretical constructions related to how Green AI can fit within future governance systems for Sustainable AI Ecosystems and their effect on organizational policies concerning sustainability. This stepwise design effectively combines the high-level perspectives derived from Policy and Scholarly literature with the detailed evidence collected through Organizational practices and expert perspectives, thereby enhancing the overall credibility, dependability, and depth of the analysis of the Study (Creswell & Plano Clark, 2018). By synthesizing these multiple sources of evidence, the Study provides a more complete understanding of the Interpretation and Implementation of Green AI Principles and the role they may play in developing future governance frameworks for Sustainable AI Ecosystems.

Literature and regulation assume technological readiness, while empirical analysis shows that this readiness is partial, fragmented, and person-centered. The synthetic comparison of findings from the literature (SLR), regulatory framework analysis, and empirical interview data highlights a distinct discontinuity between theory, policy, and organizational practice regarding the adoption of Green Artificial Intelligence.

Below you can find the synthetic cross-case analysis in a comparative, summarizing convergences, divergences, and implementing gaps by dimension regarding the three phases of the study (i) SLR / synthesized literature, (ii) findings from EU regulation analysis, and (iii) cross-case interview findings. table 20.

Table 20: Alignment of Green AI Adoption Factors Across Research, Policy, and Practice

Dimension	SLR (Literature)	Regulation Analysis (EU Framework)	Interviews / Cross-Case
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Technological	Lack of clear standards/metrics for measuring energy consumption and footprint; research cost and time as barriers; emphasis on technical optimization.	Introduces the need for documentation and indicative KPIs (e.g., energy/CO ₂ per lifecycle or use case) and links them to technical documentation (model cards, etc.), without imposing a single technical methodology for measurement/certification.	High technological readiness for AI, but low readiness for Green AI: absence of standardized Green AI design methodologies, non-systematic measurement of energy/footprint, and no integration of sustainability as a KPI.
Organizational	Leadership, resources, and a sustainability culture are identified as decisive for successful adoption; the organizational dimension acts as a central accelerator/inhibitor.	The framework presupposes organizational compliance capacity (risk management, reporting, ESG processes) and proposes linking AI KPIs with sustainability reporting (e.g., CSRD/ESRS).	Green IT/Green AI is not treated as an independent strategic choice but as: (a) a cost derivative, (b) a project/policy requirement, or (c) a limited research direction. Knowledge often remains with individuals/teams and does not translate into policies.
Institutional / Environmental	Institutional pressures and the regulatory climate affect adoption, but often remain at a general explanatory level regarding the implementation phase.	EU regulation/policy (AI Act, CSRD/ESRS, DGA, Data Act, GDPR, EU Taxonomy, Energy Policy, etc.) acts as an external behavior shaper: it links obligations to KPIs and organizational practices (documentation, audits, risk assessment, carbon-aware scheduling).	The institutional environment acts horizontally as a “trigger”: it activates action through funding/programs/regulatory developments, but does not guarantee stable integration. Regulatory uncertainty (especially around measuring/certifying AI sustainability) is deterrent; absence of a national strategy leads to reactive practices.
Resistance & Inhibiting Factors (IRT)	Innovation Resistance Theory interprets functional and psychological resistances (increased	The regulatory framework does not explicitly capture resistance mechanisms; it presupposes rational compliance and sufficient capabilities.	The strongest resistances are organizational/social: (1) resistance to change due to workload and bias

cost/effort, value
uncertainty, fear of
change) as critical to
adoption.

toward established
practices, (2) lack of
skills/training
(technical and
managerial), (3) value
uncertainty (difficulty
in quickly quantifying
benefits). Critical
finding: “passive
resistance” via
indefinite
postponement due to
lack of
incentives/pressures.

According to various sources, the measurement of energy/CO₂ is essential and an immature activity. Sources agree that there is a disconnect between the regulatory environment and “real world” organizations, where there are limited institutional (policies, KPIs) and procedural mechanisms in place to support the transfer or implementation of the responsibility to the organizations that it affects. This gap between technological capabilities and organizational readiness reflects an implementation gap for Green AI since it is generally person/project centric. The primary barrier to adoption of Green AI is passive resistant behaviours, even when there are no explicit acts of rejection

4.5.1 Technological Dimension (Technology)

The analysis of the ‘Technological Dimension’ confirmed the findings of other studies that the lack of a clear standard for measuring Energy Consumption and the time to conduct research posed a barrier to using Green AI (Strubell et al., 2019; Henderson et al., 2020; Schwartz et al., 2020). The literature describes Green AI primarily as a technological problem of computational optimization and as a need to develop shared metrics and measurement standards. Regulatory analysis correspondingly translates this need into documentation requirements and indicative indicators (KPIs) that can be embedded into technical artefacts (e.g., extended model cards, technical documentation, continuous risk assessment).

However, empirical findings show that, despite the existence of technical infrastructure and AI expertise, organizations lack standardized Green AI-by-design methodologies and processes for systematic measurement of energy/environmental footprints. Technological readiness for AI clearly exceeds readiness for Green AI, with the result that sustainability is not integrated as a measurable objective or KPI.

4.5.2 Organizational Dimension - Organizational Integration and Readiness Asymmetry

The analysis of the 'Organizational Dimension' confirmed that Organizational Dimension was identified as a key contributor to the success of Green AI Adoption and emphasized the importance of Leadership, Resource availability, and Sustainability Culture to the successful adoption of Green AI (Tornatzky and Fleischer, 1990; Eccles et al., 2014; Kotsantonis et al., 2016).

At the organizational level, the SLR places particular emphasis on the role of leadership, resource availability, and a sustainability culture as critical determinants of successful adoption. The regulatory framework assumes that organizations can incorporate compliance obligations into governance and reporting processes, e.g., linking AI KPIs with CSRD/ESRS.

Yet cross-case findings show that Green AI does not appear as an institutionalized practice in any type of organization, but rather as a transitional and emerging domain with heterogeneous maturity. Often, knowledge is concentrated in individuals or teams and does not transform into organizational policies, while sustainability is treated as: (a) a cost derivative, (b) a project/program requirement, or (c) a limited research direction.

4.5.3 Environmental and Institutional Dimension (Environment)- Catalyst for Action, not a Stabilization Mechanism

The analysis of the 'Environmental and Institutional Dimensions' confirmed that Institutional Pressure and the Regulatory Climate have a large effect on the Green AI Adoption Process, although they have traditionally allowed for a less detailed or general level of explanation during the implementation phase (DiMaggio and Powell, 1983; European Commission, 2021; Floridi and Cowls, 2021). The institutional/policy environment acts horizontally as an external behavior shaper, linking the adoption of Green AI practices to European programs, funding instruments, and regulatory developments. Regulation can function as a strong catalyst for initiating action.

Nonetheless, empirical synthesis indicates that external pressure activates actions but does not ensure sustainable embedding: regulatory uncertainty around measuring/certifying the sustainability of AI systems is deterrent, while the absence of a national strategy leads organizations toward reactive rather than proactive practices.

4.5.4 Analysis of Resistance and Inhibiting Factors (Innovation Resistance Theory)

Innovation Resistance Theory provides an interpretative framework for understanding the functional and psychological resistance observed in organizations (Ram & Sheth, 1989; Kalmus & Nikiforova, 2024). The theoretical lens of Innovation Resistance Theory helps explain why organizations, even when recognizing the importance of sustainability, do not proceed to institutionalized adoption of Green AI. Empirical findings

show that resistance manifests primarily as organizational/social rather than purely technical. The most critical form is “passive resistance” in that organizations do not explicitly reject adoption, but postpone it indefinitely due to lack of incentives, limited resources, or uncertainty about immediate value.

Overall, the cross-case synthesis shows that Green AI does not fail primarily due to technical inadequacy, but due to institutional, organizational, and knowledge discontinuities. The transition to sustainable AI ecosystems requires simultaneous maturation of technological practices, organizational structures, and policy/regulatory frameworks, so that sustainability is transformed from a project-centered exception into a systematic organizational property.

4.6 Linking Findings to the Green AI Adoption Framework

The synthesis of the results points to the need to develop a **holistic Green AI Adoption Framework**, which incorporates the full AI life cycle, combines technological, organizational, and environmental factors (TOE), considers resistance mechanisms and inhibiting factors (IRT), interprets the role of institutional pressures and legitimization (Institutional Theory).

The proposed framework bridges the gap between policy and practice by translating EU strategic directions into applicable organizational and technological practices.

Table 21: From EU Regulation to Practice: Sustainability KPIs and Organisational Responses for Green AI

Regulatory Framework	Indicative Sustainability KPIs	Organisational & Technical Practices
AI Act	Energy consumption per model lifecycle; CO ₂ emissions per AI use; AI risk indicators	Integration of environmental KPIs into technical documentation; extension of model cards; continuous risk assessment
Contextual AI Act	Energy footprint per use case; scalability efficiency	Impact mapping per AI application; low-carbon use-case design
CSRD / ESRS	Total ICT energy consumption; Scope 2 & 3 emissions; digital sustainability indicators	Integration of AI KPIs into sustainability reporting; linkage between AI documentation and ESG reports
Data Governance Act (DGA)	Data quality, availability and security indicators	Documented data-sharing processes; access control and audit mechanisms
Data Act	Data use efficiency; interoperability indicators	Workflows for fair access and reuse of data

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GDPR	Data protection compliance indicators; number of data breaches	Privacy-by-design processes; data protection controls embedded in MLOps
EU Taxonomy	Alignment rate with environmental objectives	Assessment of AI and ICT infrastructures against sustainability criteria
EU Energy Policy	Infrastructure energy efficiency; CO ₂ reduction rates	Carbon-aware workload scheduling; compute budget approval processes

Table 21 illustrates how key European Union regulatory frameworks can be aligned with indicative sustainability performance indicators (KPI), and how these indicators may support the management of artificial intelligence systems. This analysis attempts to connect the legislative requirements identified in the regulatory frameworks to the actual processes used to implement them in an organization, and highlights the relationship between compliance obligations, practices, and measurable and verifiable outcomes. Additionally, the study discusses environmental performance indicators related to the AI Act and the Corporate Sustainability Reporting Directive (CSRD) in addition to how data governance provides interoperability between sustainability and risk management.

Furthermore, the table demonstrates how Environmental Performance Indicators related to the AI Act and Corporate Sustainability Reporting Directive (CSRD) could be operationalized in real life, along with examples of how many data governance mechanisms support interoperability between AI Risk Management and Sustainability Reporting.

4.7 Implications of Findings for the Green AI Adoption Framework

The findings demonstrate a pressing need for a systematic adoption framework addressing the whole life cycle of AI and including the relationship between public policy and actual implementation (Floridi et al., 2019; UNESCO, 2021).

To meet these objectives, this framework integrates different theoretical bases regarding Green AI. The framework includes three complementary theories: Technology-Organization-Environment (TOE) model; Institutional Theory; and Innovation Resistance Theory (IRT) at three separate levels of analysis. Therefore, it can be utilized as frameworks to interpret the nature of Green AI adoption from a comprehensive perspective by examining the extent of technological readiness, how organizations respond to it, how institutions impact it, and how various forms of resistance will manifest.

Table 22: Explicit Mapping to TOE – Institutional Theory – Innovation Resistance Theory (IRT)

Level of Analysis	TOE Framework	Institutional Theory	Innovation Resistance Theory (IRT)
Technological	Technological (T) • Universal recognition of the need for energy and CO₂ measurement metrics/standards. • Gap between AI infrastructure availability and Green AI-by-design practices. • Absence of systematic measurement and integration of sustainability KPIs.	Mimetic pressures • Limited imitation due to lack of mature Green AI standards and benchmarks. • Uncertainty around certification and measurement frameworks.	Functional resistance • Cost and workload associated with measurement and documentation. • Lack of tools and methodologies for standardized practice.
Organizational	Organizational (O) • Critical role of leadership, resources, and sustainability culture. • Reliance on person-centered knowledge; absence of formal policies and standardized procedures. • Green AI treated as a project requirement or cost factor rather than a strategic priority.	Normative pressures • Strengthening ESG discourse and stakeholder sustainability expectations. • Emergence of digital sustainability as a normative organizational expectation.	Passive resistance • Postponement of adoption without explicit rejection. • Delays driven by limited resources and weak incentives.
Environmental / Institutional	Environmental (E) • EU regulation and funding instruments as external drivers. • Regulatory uncertainty regarding AI sustainability	Coercive pressures • Compliance and reporting obligations (AI Act, CSRD/ESRS, GDPR, etc.). • Linkage of requirements to	Psychological resistance • Value uncertainty and difficulty in rapidly quantifying benefits. • Bias toward

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measurement and certification.

- Absence of a national strategy leading to reactive adoption.

documentation and measurable KPIs.

established practices and fear of change.

This image (Figure 4) visually depicts an Integrated Green Artificial Intelligence Adoption Framework, showing the technological, organizational and environmental/institutional factors that influence the adoption of Green Artificial Intelligence. Resistance to innovation is included as articulated by Innovation Resistance Theory (IRT), showing how these dimensions function together to lead to sustainability-oriented results such as reducing environmental footprint, responsible governance of AI and increasing public confidence and institutional legitimacy.

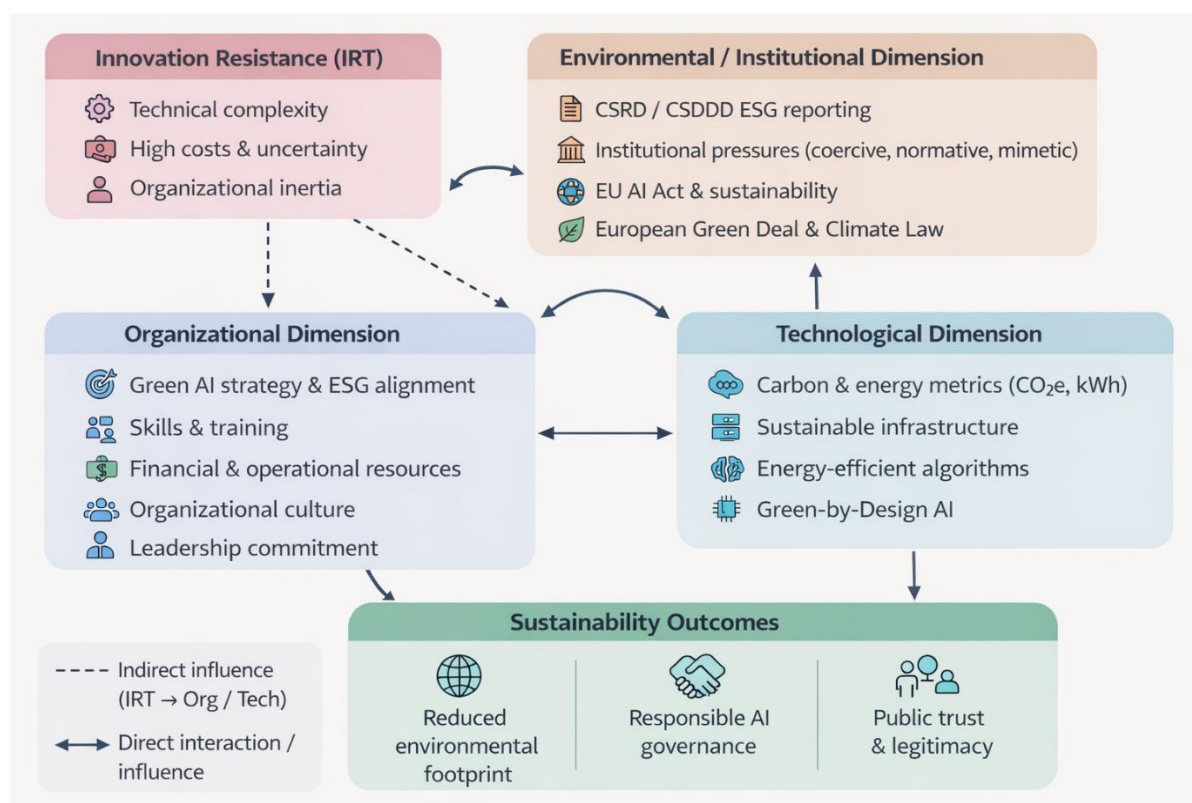


Figure 4. Green Artificial Intelligence Adoption Framework

This following figure presents a compact and vertically structured representation of the dual sustainability logic of Green Artificial Intelligence. The *Green-by-Design* loop captures internal efficiency improvements

across the AI lifecycle, while the *Green-via-AI* loop illustrates how AI systems enable broader sustainability, ESG, and policy objectives. The vertical arrangement highlights the conceptual bridge between technological design choices and policy-driven sustainability outcomes, emphasizing their reciprocal reinforcement.

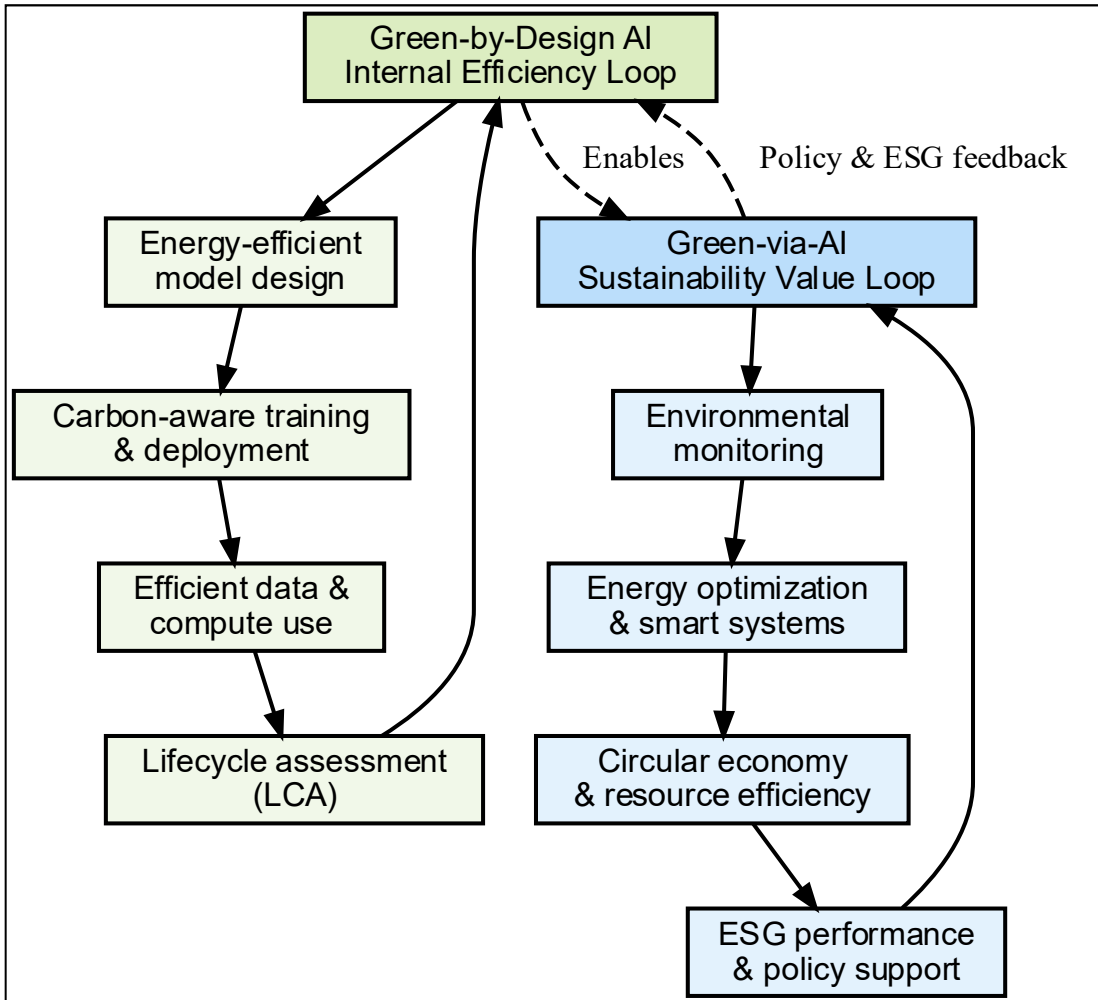


Figure 5. Vertical Green-by-Design and Green-via-AI Sustainability Loops

4.8 Chapter Summary - Research Question Alignment and Coverage

Green Artificial Intelligence (AI) is seen by researchers as being an up-and-coming area of research and policy, rather than an established technology or type of organization in literature. Contributions to foundational literature describe Green AI as normative, demonstrating a shift toward using the resources efficiently, being accountable in the way AI operates, and working toward protecting our natural resources through the way AI is developed. The contributions in the foundational literature do so using principles they suggest that need to be followed, as well as identifying actions that need to be taken, as opposed to having well-established standards or structures that can help implement Green AI in an organizational form

(Schwartz et al., 2020). Other studies continue to highlight that currently there are no widely accepted or standard ways to measure the effect that AI has on the economy, environment and social issues, and the ways to measure if AI accomplishes these effects is fragmented and inconsistent within studies or types of AI (Strubell et al., 2019; Henderson et al., 2020). Furthermore, the reports from a policy perspective and from organizations indicate that the bulk of the work and initiatives related to implementing Green AI are happening only in research institutions and through pilot and experimental projects, which provides very little evidence of Green AIs being widely adopted within organizations or in a systematic manner (OECD, 2022; European Commission, 2023). Literature continues to identify that there are many ongoing challenges with governance, operationalization and regulatory clarity, and therefore there are no established institutional structures in place that will support the widespread use of and sustained implementation of Green AI within organizations (OECD, 2022).

Collectively, these characteristics—conceptual ambiguity, lack of standardized metrics, fragmented practices, and limited organizational embedding—are widely recognized indicators of a field that, despite its growing prominence, has not yet reached a high level of technological or organizational maturity (Schwartz et al., 2020; Henderson et al., 2020). The strong dependence on European policies suggests that adoption is not yet an endogenous choice of sustainability strategy, but rather externally driven.

Consistent with this characterization, the empirical findings of the present study reveal fragmented adoption patterns, strong dependence on external policy drivers, and limited organizational integration of Green AI practices.

The emphasis placed on education, pilot projects, and tangible examples of implementation demonstrates that trust and acceptance of Green AI are built primarily through practical experience rather than a theoretical approach.

Finally, not adopting Green AI is not considered a neutral choice, but is associated with long-term risks of losing credibility, innovation, and competitiveness.

According to the findings of this study, the research question was answered in totality by identifying through systematic analysis, the major drivers/obstacles as well as the main regulatory frameworks that impact the adoption of Green AI across organizational, technological, and environmental dimensions. Qualitative evidence demonstrates that the adoption of Green AI is significantly impacted by a combination of key internal organizational capabilities and readiness to accept new technologies, as well as economic considerations, policy incentives, and strategic objectives that will drive the adoption of this type of technology. Meanwhile, while there are indeed some economic/technical limitations to the adoption of Green AI, many more limitations arise from lack of organizational support/resistance to change, as well as

skills gaps, confusion over how to implement it effectively at an organization level, and uncertainty about what types of results or benefits one will receive from implementing any Green AI initiatives. In addition, this work highlights the critical importance of institutional and policy environments, especially at the EU level, in shaping behavior (or lack thereof) at the organizational level, and, while highlighting some of the significant gaps regarding lack of national-level coordination and regulatory clarity between the EU and individual Member States on GAI, it also provides guidance to decision-makers throughout Greece and the EU regarding sustainable Green AI adoption practices and governance structures. Thus, these findings provide both actionable and executable implications for policymakers and organizational decision-makers, concerning the design of coherent legislative frameworks and organizational strategies that will align technological innovation with a sustainable environment. The study found that the research question was addressed through a structured examination of aspects like drivers, barriers, and regulations that influence the uptake of Green Artificial Intelligence from an organization, technology, and environmental perspective. The qualitative data shows that the uptake of Green AI is linked with three types of influences, namely: (1) internal organization capabilities, (2) technological readiness, (3) external institutional pressures, along with three main driving influences, which included (1) economic considerations, (2) policy incentives, and (3) strategic objectives. Additionally, the findings show that the limitations to uptake were primarily organizational resistance, skills gaps, conceptual ambiguity, and uncertainty about the value and outcome of Green AI initiatives and less on technical limitations. Additionally, the findings reveal the importance of the institutional and policy environment (particularly at the EU-level) in influencing behavior within organizations. Findings also identified significant gaps in national-level coordination and clarity in regulations. By aggregating findings from multiple cases, with a multidimensional analytic lens the study offers empirical evidence to inform the development of sustainable governance mechanisms and practices for Green AI uptake and offers insight into practical implications for policymakers and decision-makers in both Greece and the EU, including support to develop coherent governing frameworks and strategies that coordinate technological innovation with economic development sustainability objectives.

The analysis of this Chapter 4 demonstrates that Green AI adoption will require collaboration among different governance and organization strategy levels through a coordinated effort (Jobin et al., 2019; European Commission, 2020). It is both a **technological and institutional challenge**. Its effective adoption requires the systematic alignment of policy, technology, and organizational capacity. The findings of this chapter provide a detailed basis for the development of the Green AI Adoption Framework and set the stage for the discussion and policy recommendations that follow in the next chapter.

5. Conclusions

This chapter transforms the theoretical underpinnings from the above paragraph into a conceptual framework and a semi-structured interview instrument that explores organizational practices, drivers, and barriers in adopting Green AI responsibly. It is proposed that a conceptual framework combining the internal organizational aspects of the TOE and the external institutional forces of Institutional Theory can be developed to investigate the relationship between technological, organizational, and environmental attributes, and institutional pressures in shaping the impact of responsible artificial intelligence governance and sustainability outcomes for examples see (Kirivan 2025; Nikiforova 2025). The proposed conceptual framework identifies how the technologic readiness, culture of the organization, and availability of resources will intersect with the coercive, normative, and mimetic pressures associated with Green AI, thus defining both the level of adoption of Green AI and the quality of implementation. See Anomah 2025; Kirivan 2025. It is argued that responsible governance mediates these relationships-translating adoption practices into measurable sustainability outcomes. The institutional framework of the TOE aims to provide insight into which areas will yield the greatest results from various policy interventions. These findings will be used for improving the ability of regulatory harmonization between sustainability and artificial intelligence governance, generating standardized metrics for Green AI and enhancing the capability of developers of both sectors through their respective organizations. This will contribute to the European and global agenda for the responsible, transparent, and sustainable deployment of AI, such as Nikiforova 2025 and Anomah 2025.

5.1 Framework for Adopting Green Artificial Intelligence

The adoption of Green AI is emerging as a multidimensional and systemic undertaking, which is not limited exclusively to optimization techniques, but requires the combined maturation of technological, organizational, and institutional parameters. Based on the synthesis of the systematic literature review (SLR), the analysis of the European regulatory framework, and empirical findings, the adoption of Green AI is effectively interpreted through the Technology–Organization–Environment (TOE) framework.

At the technological level, there is a high degree of maturity in terms of energy consumption and carbon footprint measurement tools, as well as algorithm optimization techniques. Nevertheless, sustainability is not systematically incorporated as a design principle (Green-by-Design), and there is a lack of standardized models and binding performance indicators. At the organizational level, adoption depends heavily on leadership commitment, skill availability, and sustainability culture, but knowledge often remains person-centric and is not translated into institutionalized strategy. At the institutional level, the European regulatory

framework acts primarily as an external pressure mechanism, with an emphasis on transparency rather than binding energy efficiency requirements at the model level.

5.2 Policy and Strategy Implications and Recommendations

At the public policy level, it is necessary to establish binding Green AI indicators relating to energy consumption and CO₂ emissions throughout the entire life cycle of AI systems, including the inference phase. At the same time, the AI Act needs to be strengthened with measurable environmental requirements and harmonized with existing regulatory tools such as the CSRD, the Energy Efficiency Directive, and the EU Taxonomy. The provision of incentives, combined with the integration of Green AI criteria into public procurement, can act as a catalyst.

At the organizational level, it is recommended to incorporate sustainability indicators into technical documentation (model cards), MLOps processes, and ESG reports, as well as to create Green AI governance structures, while investing in training and pilot projects.

The concept of Green AI in Greece is emerging not only as a technical challenge, but also as an organizational and institutional transition, the success of which depends on the convergence of technology, people, and policies.

The model illustrates how Green AI implementation emerges from the interaction between technology and organizational readiness, perceived barriers and resistance, and the institutional and policy environment. Adoption is conceptualized as a continuous and dynamic process shaped by internal and external factors.

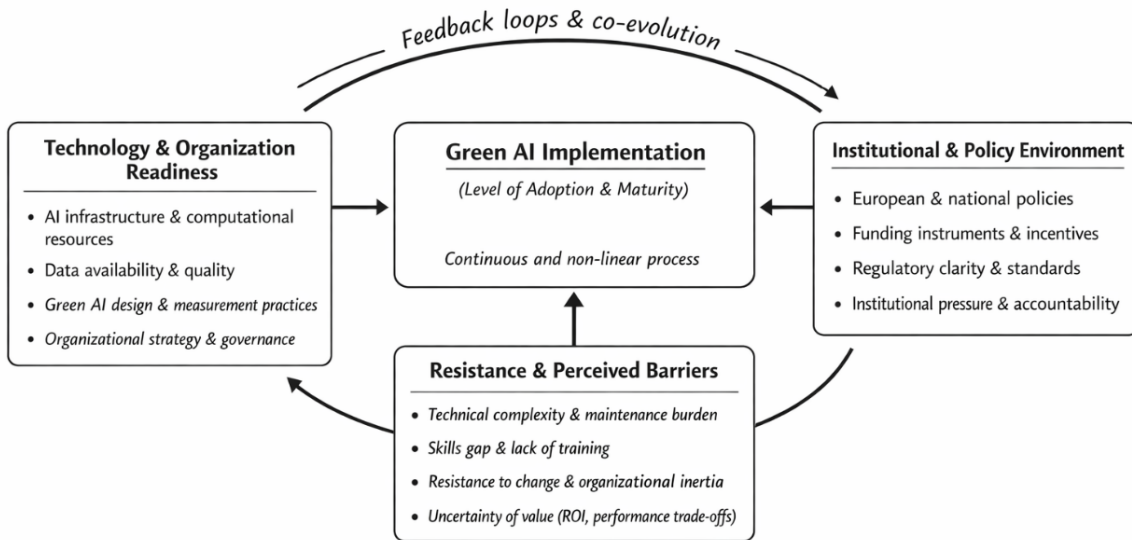


Figure 6: Green AI implementation is shaped by the interplay of readiness, barriers, and the institutional environment.”

The key recommendations concern the transition from fragmented and project-centric practices to the systematic adoption of Green AI, the standardization of measurement methodologies, and the linking of environmental costs to model performance. However, implementation is limited by the lack of universally accepted benchmarks, regulatory uncertainty at the inference and full life cycle levels, and the risk of carbon leakage due to international regulatory asymmetries.

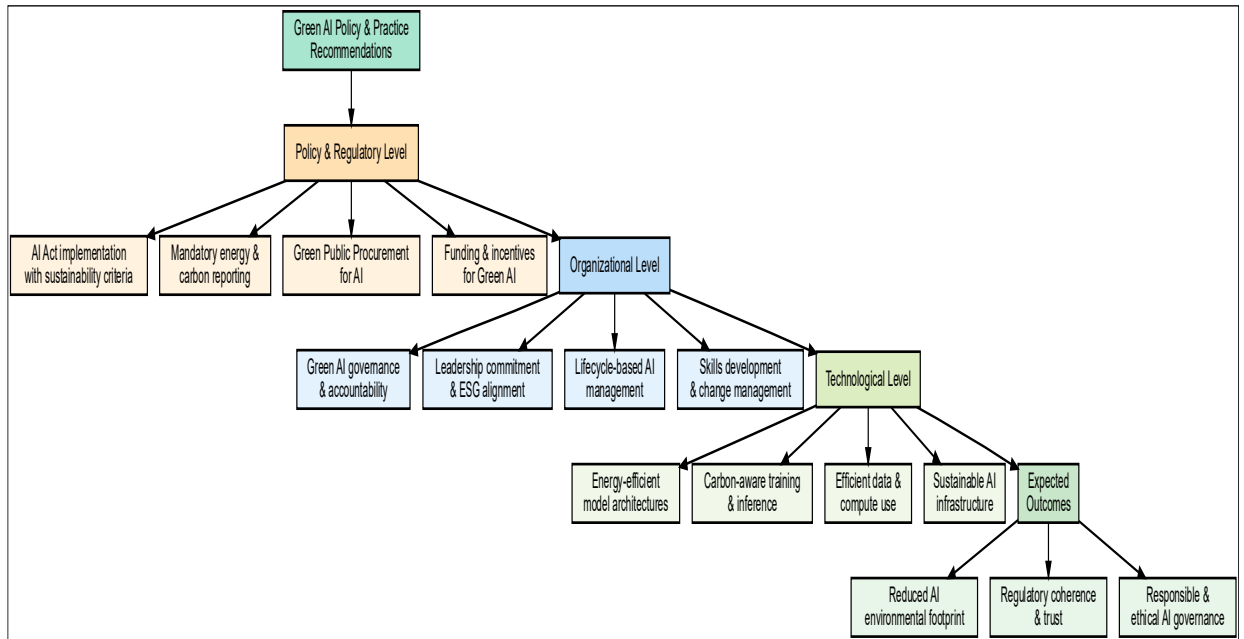


Figure 7. Structured Policy and Practice Recommendations for Green AI Adoption

A detailed and coherent structure has been developed from the above findings to establish composed consolidated sets of recommendations related to Policies & Regulations, Organizations, and Technology for Green AI to contribute toward developing a coherent framework for Green AI's adoption based on guidance provided at different Policy, Organization & Technology Levels: from governance through to institutional alignment and finally following through to technical implementation and resulting in Sustainable Outcomes.

5.3 Limitations

Despite the advantages of the mixed methods methodology in terms of its holistic approach to the subject, this research is subject to certain limitations:

- **Geographical specificity:** The focus on the Greek context, which is characterized by low rates of digital transition, limits the possibility of directly generalizing the conclusions to countries with different digital characteristics.
- **Sampling limitations:** Although the sample size in the interviews ensured thematic adequacy, it may not represent the full range of opinions, especially regarding SMEs.
- **Research subjectivity:** The interpretation of qualitative data inevitably bears the imprint of the researcher's perspective.
- **Temporal dynamics:** Due to rapid changes in technological issues and rapid developments in emerging technologies, the results reflect the current situation and require constant updating.

To compensate for these limitations, several methodological safeguards were implemented such as the triangulation of multiple data sources (policy, literature, and interviews) enhanced validity. Audit trails of data coding and synthesis were maintained to facilitate reproducibility. By combining these strategies, the study maintains high standards of **ethical responsibility, methodological rigor, and transparency**, in line with the principles of **Green AI** that underpin its theoretical framework.

The limitations of this study include: The number of interviews (eleven total) - while enough to provide in-depth qualitative analysis, it does not allow for statistical generalization of findings; The research was conducted using participant self-reports and may be impacted by their individual experience or the organizational role; and The rapid growth of Green AI provides an environment where new technologies or regulations could change the implications of some of the findings in this study.

5.4 Future Research Directions

Future research should focus on the development of standardized Green AI metrics, the sustainability of the inference phase, organizational models of Green AI governance, economic cost-benefit assessment, and comparative international studies that explore regulatory convergence and divergence. Future research directions include, Investigating the use of quantitative or mixed methods for determining the adoption level of Green AI to better understand the generalizability of findings. Creating and testing indicators to measure sustainability associated with the implementation of AI at the organizational level. Comparing adoption across different countries or institutional settings. Examining the characteristics of organizations' transitions from Green AI pilot programs to mature practices. Studying how the decisions made by decision makers help organizations prepare for both technological readiness and organizational readiness.

More specifically, the **conceptual framework of developing measurable green AI governance** will be established via the transition from conceptual frameworks to measurable governance tools, via distinct operationalization and/or measurement of green AI governance. In addition to creating an integrated framework for the adoption of green AI governance, future research directions may involve developing metrics for the adoption of the components of green AI governance so that they can be used as performance metrics to assess green AI governance performance through organizational assessment tools, audits, or regulatory reporting requirement mechanisms. This will create a pathway for the transition of analytical governance models into actionable green AI governance instruments, especially for use by decision makers and government agencies.

Because **Green AI is an ongoing dynamic progression** rather than something that can simply be adopted once, future research could change its view as a dynamic path-dependent event rather than simply making

a fixed choice. Temporal research designs could look into the growth of organizations from their first use of Green AI through to their use of established, mature, institutionalized forms of Green AI practice by identifying key transition points, learning methods, and lock-in effects. Taking this type of approach would enhance the tracking of how long-term events are tracked within the framework of sustainable AI governance.

Bridging the gap between AI regulations and environmental policies will be an important research area for future study. The existing regulatory gaps between AI governance and environmental regulations is an important issue to research. Although sustainability is increasingly being considered across digital policies as a whole - it is still divided between various separate regulatory bodies. To help build a larger understanding of potential for these three areas of regulation - future research should include studies analyzing specific AI-based regulations; energy policies; and how individual government sustainability reporting frameworks work together. This research could assist in creating more cohesive policy architecture designed specifically to promote Green AI.

Organizational Power, Responsibility, and Accountability in Green AI, Research on future use of Green AI should include considerations of support, responsibilities/consequences, and areas for improvement in areas of organizational power that may be employed in developing and implementing Green AI. In future research there may need to be an examination of who will have the authority to make sustainability decisions related to AI systems; how accountability for environmental impacts will be assigned in the area of organization; and if there are specific governance structures that help to mediate between efficiency and performance and environmental sustainability in all of these types of systems and organizations.

Green AI in the Public Sector as a Distinct Governance Challenge, as one of the newest governance challenges of Green AI in the public sector, a promising area for systematic research is to examine both how Green AI principles are being operationalized in public sector AI use cases and to look at ways that governments can be both policy regulators and best practice demonstrators in sustainable AI data and technology practices. One area for future research could be in examining how Green AI principles are being implemented in both state and local purchasing guidance around AI data and technology.

Trade-Offs Between Performance, Ethical Principles, and Sustainability Management, finally, future research will more directly involve the trade-offs of sustainable AI governance. Green AI often does not align with performance optimization, vice versa, ethically fair objectives and innovation speed will not be mutually inclusive. To understand responsible AI in a realistic and normative manner, researchers should study how organizations/policymakers manage these tensions rather than focusing solely on single-objective optimization.

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7. Appendix

Appendix A – questionnaire in Greek

Πρωτόκολλο Συνέντευξης

ΕΙΣΑΓΩΓΗ

Σας ευχαριστώ για τη συμμετοχή σας στην παρούσα μελέτη που σχετίζεται με την διερεύνηση των πρακτικών υιοθέτησης της Πράσινης Τεχνητής Νοημοσύνης (Green Artificial Intelligence – Green AI).

Η πράσινη τεχνητή νοημοσύνη (Green AI) αναδύεται ως:

- **ένα τεχνολογικό πρότυπο** — εστιασμένο στη μείωση του ενεργειακού, του ανθρακικού και του υπολογιστικού κόστους των συστημάτων τεχνητής νοημοσύνης, και
- **ένα πρότυπο διακυβέρνησης και πολιτικής** — ενσωματώνοντας αρχές βιωσιμότητας στη ρύθμιση, τη στρατηγική και την ηθική ευθύνη της τεχνητής νοημοσύνης.

Ο πιο ευρέως αποδεκτός ορισμός, που συνθέτει αυτές τις προοπτικές, μπορεί να διατυπωθεί ως εξής:

Η πράσινη τεχνητή νοημοσύνη (πράσινη TN) είναι η πρακτική του σχεδιασμού, της ανάπτυξης και της εφαρμογής συστημάτων τεχνητής νοημοσύνης που μεγιστοποιούν την κοινωνική και οικονομική αξία, ελαχιστοποιώντας παράλληλα τις περιβαλλοντικές επιπτώσεις μέσω ενεργειακά αποδοτικών αρχιτεκτονικών, υπεύθυνης χρήσης δεδομένων και μηχανισμών διακυβέρνησης που εξασφαλίζουν τη βιωσιμότητα και τη διαφάνεια σε όλο τον κύκλο ζωής της τεχνητής νοημοσύνης.

Σκοπός του παρόντος πρωτοκόλλου συνέντευξης είναι η διερεύνηση των παραγόντων που επηρεάζουν την υιοθέτηση της Πράσινης TN (Green AI), με έμφαση σε τεχνολογικούς, οργανωτικούς και θεσμικούς παράγοντες, καθώς και σε παράγοντες αντίστασης, με στόχο την υποστήριξη της ανάπτυξης ενός υπεύθυνου πλαισίου υιοθέτησης και χάραξης πολιτικής για την Πράσινη TN.

Όπως σε κάθε διαδικτυακή δραστηριότητα, υπάρχει πάντοτε η πιθανότητα παραβίασης δεδομένων. Στο μέτρο του δυνατού, οι απαντήσεις σας θα παραμείνουν εμπιστευτικές. Τα δεδομένα θα χρησιμοποιηθούν σε ανωνυμοποιημένη μορφή και τα προσωπικά σας δεδομένα (ονοματεπώνυμο, υπογραφή και διεύθυνση ηλεκτρονικού ταχυδρομείου) θα διαγραφούν εντός έξι (6) μηνών από την ολοκλήρωση της συλλογής δεδομένων.

Η συμμετοχή σας στη μελέτη είναι απολύτως εθελοντική. Μπορείτε να αποχωρήσετε οποιαδήποτε στιγμή χωρίς καμία συνέπεια και μπορείτε να παραλείψετε οποιαδήποτε ερώτηση.

Η συνέντευξη θα διαρκέσει περίπου 40 λεπτά. Θα σας θέσω 28 ερωτήσεις, ξεκινώντας με γενικές ερωτήσεις που αφορούν τον οργανισμό στον οποίο ανήκετε και θα συνεχίσουμε με ανοιχτές ερωτήσεις σχετικά με τα εμπόδια που έχουν εντοπιστεί για την υιοθέτηση της Πράσινης TN (Green AI) στον οργανισμό σας. Η συνέντευξη θα ολοκληρωθεί με μερικές γενικές ερωτήσεις σχετικά με το πλαίσιο πολιτικής που ισχύει στη χώρα σας.

Η παρούσα μελέτη διεξάγεται στο πλαίσιο του μεταπτυχιακού προγράμματος σπουδών με τίτλο «Ηλεκτρονική Διακυβέρνηση» του Τμήματος Μηχανικών Πληροφοριακών και Επικοινωνιακών Συστημάτων, του Πανεπιστημίου Αιγαίου, με επιβλέποντα τον Αναπλ. Καθ. Χ. Αλεξόπουλο.

ΕΝΗΜΕΡΩΤΙΚΗ ΣΥΓΚΑΤΑΘΕΣΗ

ΠΑΡΑΚΑΛΩ ΣΗΜΕΙΩΣΤΕ ΤΟ ΚΑΤΑΛΛΗΛΟ ΠΛΑΙΣΙΟ	Yes	No
A: ΓΕΝΙΚΗ ΣΥΜΦΩΝΙΑ – ΣΤΟΧΟΙ ΕΡΕΥΝΑΣ, ΚΑΘΗΚΟΝΤΑ ΣΥΜΜΕΤΕΧΟΝΤΑ ΚΑΙ ΕΘΕΛΟΝΤΙΚΗ ΣΥΜΜΕΤΟΧΗ		

ΠΑΡΑΚΑΛΩ ΣΗΜΕΙΩΣΤΕ ΤΟ ΚΑΤΑΛΛΗΛΟ ΠΛΑΙΣΙΟ	Yes	No
1. Δηλώνω ότι έχω διαβάσει και κατανοήσει πλήρως τις πληροφορίες της μελέτης ή ότι αυτές μου έχουν αναγνωσθεί	☐	☐
2. Συμμετέχω εθελοντικά και γνωρίζω ότι μπορώ να αποχωρήσω οποιαδήποτε στιγμή χωρίς αιτιολόγηση	☐	☐
3. Κατανοώ ότι η συνέντευξη θα ηχογραφηθεί, θα απομαγνητοφωνηθεί και στη συνέχεια η ηχογράφηση θα διαγραφεί.	☐	☐
4. Κατανοώ ότι η μελέτη θα ολοκληρωθεί μετά τη διεξαγωγή επαρκούς αριθμού συνεντεύξεων σε διάφορους οργανισμούς, ακαδημαϊκούς φορείς, τον δημόσιο τομέα και τη βιομηχανία στην Ελλάδα, με σκοπό τη βελτίωση του μοντέλου και την εφαρμογή του. Η αναμενόμενη ημερομηνία ολοκλήρωσης της μελέτης είναι ο Μάρτιος του 2026		
B: ΠΙΘΑΝΟΙ ΚΙΝΔΥΝΟΙ ΣΥΜΜΕΤΟΧΗΣ ΚΑΙ ΠΡΟΣΤΑΣΙΑ ΔΕΔΟΜΕΝΩΝ		
5. Κατανοώ ότι η συμμετοχή στη μελέτη συνεπάγεται επίσης τη συλλογή συγκεκριμένων προσωπικών δεδομένων δηλ. το όνομά σας και την υπογραφή σας στο παρόν έντυπο συγκατάθεσης, καθώς και τη διεύθυνση ηλεκτρονικού ταχυδρομείου σας και συναφών προσωπικών δεδομένων έρευνας (δηλ. τον οργανισμό σας), με τον ενδεχόμενο κίνδυνο αποκάλυψης της ταυτότητάς μου.	☐	☐
6. Κατανοώ ότι θα ληφθούν τα ακόλουθα μέτρα για την ελαχιστοποίηση του κινδύνου παραβίασης δεδομένων και την προστασία της ταυτότητάς μου σε περίπτωση τέτοιας παραβίασης, μέσω της ανωνυμοποίησης των δεδομένων και της χρήσης τους κυρίως σε συγκεντρωτική μορφή. Οι ηχογραφήσεις θα μεταγραφούν (με πρόσβαση μόνο στην ομάδα της μελέτης), ενώ οι ηχογραφήσεις θα διαγραφούν μετά τη μεταγραφή. Οι μεταγραφές θα ανωνυμοποιηθούν και θα αποθηκευτούν τοπικά και με ασφάλεια. Θα αναφερθούμε μόνο σε οργανισμούς όπου απασχολούνται οι ερωτηθέντες με συγκεντρωτικό τρόπο και τα αποσπάσματα στις δημοσιεύσεις μας θα ανωνυμοποιηθούν	☐	☐
7. Κατανοώ ότι τα προσωπικά στοιχεία που συλλέγονται για μένα και τα οποία μπορούν να με ταυτοποιήσουν, όπως το όνομά μου, δεν θα κοινοποιηθούν εκτός της ερευνητικής ομάδας.	☐	☐
8. Κατανοώ ότι τα (αναγνωρίσιμα) προσωπικά δεδομένα που παρέχω θα καταστραφούν στο τέλος της έρευνας.	☐	☐
C: ΔΗΜΟΣΙΕΥΣΗ, ΔΙΑΔΟΣΗ ΚΑΙ ΕΦΑΡΜΟΓΗ ΤΗΣ ΕΡΕΥΝΑΣ		
9. Κατανοώ ότι μετά την έρευνα, οι ανώνυμες πληροφορίες που παρέχω θα χρησιμοποιηθούν για εκθέσεις, δημοσιεύσεις, ιστότοπους, καθώς και για την ανάπτυξη πολιτικών με σκοπό τη βελτίωση του τρέχοντος πλαισίου υιοθέτησης της πράσινης ΤΝ. Σε συγκεκριμένες περιπτώσεις, αναμένουμε να αναφερθούμε στις απαντήσεις που παρέχονται (ανώνυμα αποσπάσματα) για να διασφαλίσουμε την ακρίβεια των αναφορών σε συγκεκριμένα ζητήματα.	☐	☒

ΠΑΡΑΚΑΛΩ ΣΗΜΕΙΩΣΤΕ ΤΟ ΚΑΤΑΛΛΗΛΟ ΠΛΑΙΣΙΟ	Yes	No
10. Συμφωνώ ότι οι απαντήσεις, οι απόψεις ή άλλες πληροφορίες που παρέχω μπορούν να αναφερθούν ανώνυμα σε ερευνητικά αποτελέσματα.	☐	☐

Υπογραφή

Όνομα συμμετέχοντα

Υπογραφή

Ημερομηνία

Εγώ, ως ερευνήτρια, διάβασα με ακρίβεια το ενημερωτικό δελτίο στον πιθανό συμμετέχοντα και, κατά το μέτρο των δυνατοτήτων μου, διασφάλισα ότι ο συμμετέχων κατανοεί σε τι συναινεί ελεύθερα.

Όνομα Ερευνήτριας

Υπογραφή

Ημερομηνία

Στοιχεία επικοινωνίας της μελέτης για περισσότερες πληροφορίες: [Ε. Αλεξοπούλου, 6977039185– evangelia.alex@gmail.com, icsdm623001@aegean.gr]

ΕΡΩΤΗΣΕΙΣ ΣΥΝΕΝΤΕΥΞΗΣ

Ο οργανισμός σας

Θα ξεκινήσουμε τώρα τη συνέντευξη με μερικές ερωτήσεις σχετικά με τον οργανισμό για τον οποίο εργάζεστε.

E1. Σε ποιον κυβερνητικό/ιδιωτικό οργανισμό εργάζεστε; (όνομα, τομέα)
E2. Ποια είναι τα κύρια καθήκοντα του οργανισμού σας;
E3. Ποιος είναι ο ρόλος σας σε αυτόν τον οργανισμό;

Ο οργανισμός σας: Στρατηγική και ετοιμότητα για την πράσινη τεχνητή νοημοσύνη

Πολλοί οργανισμοί σήμερα χρησιμοποιούν την τεχνητή νοημοσύνη (TN/AI) και ταυτόχρονα προσπαθούν να μειώσουν τον περιβαλλοντικό τους αντίκτυπο. Η πράσινη TN (Green AI) αναφέρεται σε συστήματα AI που έχουν σχεδιαστεί και χρησιμοποιούνται με τρόπο ενεργειακά αποδοτικό και περιβαλλοντικά υπεύθυνο. Στις ακόλουθες ερωτήσεις, **εστιάζουμε στη στρατηγική, την ετοιμότητα, τους πόρους και την προετοιμασία του οργανισμού σας** για την υιοθέτηση της πράσινης τεχνητής νοημοσύνης.

E4. Έχει υιοθετήσει ο οργανισμός σας συστήματα τεχνητής νοημοσύνης (AI); ➔ Εάν ναι, προχωρήστε στην ερώτηση 5. ➔ Εάν όχι, προχωρήστε στην ερώτηση 9.
E5. Ποιοι ήταν οι κύριοι παράγοντες που οδήγησαν στην υιοθέτηση της τεχνητής νοημοσύνης στον οργανισμό σας;
E6. Είναι ο οργανισμός σας εξοικειωμένος με την έννοια της πράσινης τεχνητής νοημοσύνης;
E7. Έχει υιοθετήσει ο οργανισμός σας ή σχεδιάζει να υιοθετήσει λύσεις πράσινης τεχνητής νοημοσύνης;
E8. Τι παρακινεί ή αποθαρρύνει τον οργανισμό σας από την υιοθέτηση πράσινης τεχνητής νοημοσύνης;
E9. Τι εμποδίζει τον οργανισμό σας από την υιοθέτηση συστημάτων τεχνητής νοημοσύνης (AI) (εάν ισχύει);

Ερωτήσεις σχετικά με τα εμπόδια

Θα συζητήσουμε τώρα **διάφορους τύπους εμποδίων** που σχετίζονται με την υιοθέτηση της πράσινης TN (Green AI). Θέλουμε να κατανοήσουμε εάν και πώς αυτά τα εμπόδια συνδέονται με τον οργανισμό σας. Αυτά τα εμπόδια μπορεί να σχετίζονται με **τεχνικά, οργανωτικά, οικονομικά, ρυθμιστικά ή πολιτισμικά ζητήματα** της υιοθέτησης της Πράσινης TN.

Θα ξεκινήσουμε συζητώντας τα **εμπόδια χρήσης (usage barriers-UB)**. Τα εμπόδια χρήσης (UB) αναφέρονται στον βαθμό στον οποίο η υιοθέτηση της Πράσινης TN απαιτεί αλλαγές στην **τεχνική υποδομή, τις λειτουργικές διαδικασίες, τις πρακτικές διαχείρισης δεδομένων και τις καθημερινές πρακτικές του οργανισμού σας**.

E10. Υπάρχουν εμπόδια χρήσης που σχετίζονται με αλλαγές στις οργανωτικές πρακτικές και που παρεμποδίζουν την υιοθέτηση της Πράσινης TN; (UBn)
- Έλλειψη υψηλής ποιότητας δεδομένων για την ενεργειακά αποδοτική εκπαίδευση της TN (UB1)
- Πολυπλοκότητα της προετοιμασίας δεδομένων για μοντέλα Πράσινης TN (UB2)
- Πολυπλοκότητα του σχεδιασμού ενεργειακά αποδοτικών συστημάτων τεχνητής νοημοσύνης (UB3)
- Πολυπλοκότητα της ανάπτυξης υποδομής πράσινης τεχνητής νοημοσύνης (UB4)
- Έλλειψη τυποποιημένων διαδικασιών υλοποίησης πράσινης τεχνητής νοημοσύνης (UB5)

- Περιορισμένη διαθεσιμότητα εργαλείων και πλατφορμών πράσινης τεχνητής νοημοσύνης (UB6)
- Περιορισμένη αυτοματοποίηση για τη βελτιστοποίηση της ενεργειακής αποδοτικότητας της τεχνητής νοημοσύνης (UB7)
- Απαιτείται μεγάλη προσπάθεια για τη συντήρηση συστημάτων πράσινης τεχνητής νοημοσύνης (UB8)
E11. Υπάρχουν άλλα εμπόδια χρήσης που αποτελούν φραγμό για την υιοθέτηση της πράσινης τεχνητής νοημοσύνης από τον οργανισμό σας; (UBn)
E12. Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός σας να εφαρμόσει ενεργειακά αποδοτικές λύσεις τεχνητής νοημοσύνης;

Θα συζητήσουμε τώρα τα **εμπόδια αξίας (value barriers – VB)** που σχετίζονται με την υιοθέτηση της Πράσινης Τεχνητής Νοημοσύνης (Green AI). Στόχος μας είναι να κατανοήσουμε εάν και πώς αυτά τα εμπόδια είναι σημαντικά για τον οργανισμό σας. Τα **εμπόδια αξίας** αναφέρονται στον βαθμό στον οποίο τα **αντιληπτά οφέλη της Πράσινης ΤΝ** θεωρούνται χαμηλότερα από το κόστος της ή σε σύγκριση με εναλλακτικές λύσεις.

Για παράδειγμα, οι οργανισμοί μπορεί να θεωρούν ότι η Πράσινη ΤΝ δεν προσφέρει πάντα επαρκή λειτουργική, οικονομική ή περιβαλλοντική αξία. Μπορεί να υπάρχουν ανησυχίες σχετικά με το υψηλό κόστος υλοποίησης, υποδομών και εκπαίδευσης, καθώς και αβεβαιότητα σχετικά με την απόδοση της επένδυσης και τα μετρήσιμα οφέλη βιωσιμότητας.

Σε ορισμένες περιπτώσεις, οι οργανισμοί επενδύουν σημαντικούς πόρους στην υιοθέτηση της Πράσινης ΤΝ, ενώ τα ευρύτερα οφέλη μπορεί να ωφελούν κυρίως εξωτερικούς ενδιαφερόμενους, όπως πολίτες, πελάτες ή την κοινωνία στο σύνολό της.

E13. Υπάρχουν εμπόδια αξίας που παρεμποδίζουν την υιοθέτηση της Πράσινης ΤΝ; (VBn)
- Η Πράσινη ΤΝ προσφέρει περιορισμένα οφέλη για την κοινωνία (VB1)
- Η Πράσινη ΤΝ προσφέρει περιορισμένη επιχειρηματική αξία (VB2)
- Περιορισμοί στην ποιότητα των δεδομένων (VB3)
- Τα οφέλη για την κοινωνία είναι χαμηλότερα από το κόστος (VB4)
- Τα οφέλη για τον οργανισμό είναι χαμηλότερα από το κόστος (VB5)
- Υψηλό κόστος επένδυσης και λειτουργίας (VB6)
- Καμία προστιθέμενη αξία στις λειτουργίες (VB7)
- Οι απαιτήσεις σε πόρους υπερτερούν των οφελών (VB8)
- Η απόδοση της επένδυσης (ROI) της πράσινης τεχνητής νοημοσύνης δεν είναι σαφής
E14. Υπάρχουν άλλα εμπόδια αξίας που εμποδίζουν την υιοθέτηση της πράσινης τεχνητής νοημοσύνης από τον οργανισμό σας; (VBn)

Θα εξετάσουμε τώρα τους πιθανούς **κινδύνους (risk barriers – RB)** που συνδέονται με την ανάπτυξη και την εφαρμογή συστημάτων Πράσινης ΤΝ και θα θέλαμε να κατανοήσουμε εάν και πώς αυτοί οι κίνδυνοι σχετίζονται με τον οργανισμό σας. Οι κίνδυνοι αναφέρονται στην **αντιληπτή αβεβαιότητα** σχετικά με τις οικονομικές, λειτουργικές και κοινωνικές συνέπειες της υιοθέτησης λύσεων Πράσινης ΤΝ (π.χ. ακούσια κακή χρήση, λανθασμένα αποτελέσματα ή ερμηνείες, ανησυχίες σχετικά με την προστασία των δεδομένων, σφάλματα στην ανάπτυξη ή την εφαρμογή μοντέλων, ζητήματα ποιότητας δεδομένων και μοντέλων, συμβιβασμοί στην ενεργειακή απόδοση κ.λπ.).

E15. Υπάρχουν εμπόδια/κίνδυνοι που δυσχεραίνουν την υιοθέτηση της Πράσινης ΤΝ;
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E16. Σε ποιο βαθμό οι ακόλουθες καταστάσεις αποτελούν εμπόδια που δυσχεραίνουν την υιοθέτηση της Πράσινης ΤΝ στον οργανισμό σας:
- Δυσλειτουργία ή αναποτελεσματικότητα των συστημάτων ΤΝ (RB1)
- Ανακριβείς μετρήσεις της απόδοσης βιωσιμότητας (RB2)
- Χαμηλή εμπιστοσύνη στα αποτελέσματα της Πράσινης ΤΝ (RB3)
- Παραβιάσεις κανονισμών - Οι απαιτήσεις κανονιστικής συμμόρφωσης για την πράσινη τεχνητή νοημοσύνη δεν είναι σαφείς (RB4)
- Έκθεση ευαίσθητων δεδομένων - Η υιοθέτηση της πράσινης τεχνητής νοημοσύνης ενέχει σημαντικούς κινδύνους για την ασφάλεια και την ιδιωτικότητα των δεδομένων (RB5)
- Σφάλματα υλοποίησης (RB6)
- Βλάβη της φήμης (RB7)
- Ανταγωνιστικό μειονέκτημα (RB8)
- Οι ανταγωνιστές επωφελούνται περισσότερο (RB9)
E17. Υπάρχουν άλλα εμπόδια κινδύνου που αποτελούν φραγμό για την υιοθέτηση της Πράσινης ΤΝ από τον οργανισμό σας; Ποιοι κανονιστικοί, οικονομικοί ή ασφαλιστικοί κίνδυνοι εμποδίζουν την υιοθέτηση της Πράσινης ΤΝ (RBn);

Θα προχωρήσουμε τώρα στη συζήτηση σχετικά με τα εμπόδια που σχετίζονται με την **παράδοση (tradition-related barriers – TB)** και που εμποδίζουν την υιοθέτηση της Πράσινης ΤΝ και θα θέλαμε να κατανοήσουμε εάν και πώς αυτά τα εμπόδια σχετίζονται με τον οργανισμό σας. Τα εμπόδια που σχετίζονται με την παράδοση αναφέρονται στον βαθμό στον οποίο η υιοθέτηση της Πράσινης ΤΝ απαιτεί από τους οργανισμούς ή τους χρήστες να αλλάξουν τις καθιερωμένες αξίες, νόρμες, πρακτικές, εσωτερική κουλτούρα του οργανισμού και τρόπους εργασίας.

E18. Υπάρχουν παραδοσιακά εμπόδια που σχετίζονται με τις απαιτούμενες αλλαγές στις πρακτικές του οργανισμού σας και που αποτελούν πρόκληση για την υιοθέτηση της Πράσινης ΤΝ; (TBn)
E19. Σε ποιο βαθμό οι ακόλουθες καταστάσεις αποτελούν εμπόδιο για την υιοθέτηση της Πράσινης ΤΝ από τον οργανισμό σας:
- Τα υπάρχοντα συστήματα ΤΝ είναι επαρκή (TB1)
- Αντίσταση στην αλλαγή που επιβάλλει η βιωσιμότητα (περιβαλλοντικής, κοινωνικής ή οικονομικής) (TB2)
- Έλλειψη δεξιοτήτων Πράσινης ΤΝ (TB3)
- Έλλειψη εκπαίδευσης (TB4)
- Αντίσταση στην αλλαγή των επιχειρησιακών διαδικασιών (TB5)
E20. Υπάρχουν άλλα παραδοσιακά εμπόδια που αποτελούν εμπόδιο για την υιοθέτηση της Πράσινης ΤΝ από τον οργανισμό σας; Ποια πολιτισμικά ή δεξιοτεχνικά εμπόδια παρεμποδίζουν την υιοθέτηση της Πράσινης ΤΝ; (TBn)

Θα συζητήσουμε τώρα τα εμπόδια που σχετίζονται με την **εικόνα (image-related barriers – IB)** για την υιοθέτηση της Πράσινης ΤΝ και θα θέλαμε να κατανοήσουμε εάν και πώς αυτά σχετίζονται με τον οργανισμό σας. Τα εμπόδια που σχετίζονται με την εικόνα αναφέρονται στον βαθμό στον οποίο η Πράσινη ΤΝ θεωρείται ότι έχει μια **δυνητικά δυσμενή εικόνα**, για παράδειγμα λόγω ανησυχιών ότι η κακή απόδοση του μοντέλου, η χαμηλή ποιότητα των δεδομένων, τα παραπλανητικά αποτελέσματα ή οι ακούσιες αρνητικές συνέπειες θα μπορούσαν να **βλάψουν τη φήμη του οργανισμού ή να οδηγήσουν σε λανθασμένα συμπεράσματα και δημόσια κριτική**.

E21. Υπάρχουν εμπόδια που σχετίζονται με τις απαιτούμενες αλλαγές στις πρακτικές του οργανισμού σας και που αποτελούν πρόκληση για την υιοθέτηση στρατηγικών πράσινης τεχνητής νοημοσύνης; (IBn)
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E22. Σε ποιο βαθμό οι ακόλουθες καταστάσεις αποτελούν εμπόδιο για την υιοθέτηση πράσινης τεχνητής νοημοσύνης από τον οργανισμό σας:
- Χαμηλή πρακτική συνάφεια (IB1)
- Κίνδυνος βλάβης της φήμης (IB2)
- Κίνδυνος βλάβης της αξιοπιστίας (IB3)
- Δημόσια κριτική (IB4)
- Ο οργανισμός σας φοβάται ότι η σύνδεσή του με λανθασμένα συμπεράσματα που εξάγονται από την ανάλυση OGD από χρήστες OGD θα βλάψει τη φήμη του (IB5)
E23. Υπάρχουν άλλα εμπόδια που σχετίζονται με την εικόνα (π.χ. εμπόδια που σχετίζονται με τη φήμη) που αποτελούν εμπόδιο για τον οργανισμό σας; (IBn)
E24. Ποια εσωτερικά ή εξωτερικά εμπόδια παρεμποδίζουν τις προσπάθειές σας για την υιοθέτηση της Πράσινης ΤΝ;
E25. Οι εθνικές ή ευρωπαϊκές πολιτικές επηρεάζουν την απόφαση του οργανισμού σας να υιοθετήσει την Πράσινη ΤΝ;
E26. Ποια μέτρα πολιτικής, δράσεις ή κίνητρα θα υποστήριζαν την υιοθέτηση της Πράσινης ΤΝ;
E27. Υπάρχουν επιπλέον εμπόδια ή παράγοντες που θα θέλατε να αναφέρετε σχετικά με την υιοθέτηση της Πράσινης ΤΝ;
E28. Από τη δική σας οπτική γωνία, ποιοι είναι οι βασικοί παράγοντες για την επιτυχή εφαρμογή της Πράσινης ΤΝ;

Σας ευχαριστώ θερμά για τον χρόνο και τη συμβολή σας στη μελέτη.

Appendix B – questionnaire in English

Interview protocol

Opening Statement

Thank you for participating in this national study on Green AI adoption practices. This study is being conducted by Evangelia Alexopoulou from the University of the Aegean, Department of Information and Communication Systems Engineering.

Green AI emerges as both:

- a **technological paradigm**—focused on reducing the energy, carbon, and computational costs of AI systems, and
- a **governance and policy paradigm**—embedding sustainability principles into AI regulation, strategy, and ethical accountability.

The most widely accepted definition, synthesizing these perspectives, can be stated as: **Green AI** is the practice of designing, developing, and applying artificial intelligence systems that maximize social and economic value while minimizing environmental impact through energy-efficient architectures, responsible data use, and governance mechanisms that ensure sustainability and transparency across the AI lifecycle

The purpose of this questionnaire is to investigate the factors influencing the adoption of Green Artificial Intelligence (Green AI), focusing on technological, organizational, and institutional factors, as well as

resistance factors, aiming to support the development of a responsible Green AI adoption and policy framework.

As with any online activity, the risk of a breach is always possible. To the best of our ability, your answers in this study will remain confidential. We will minimize any risks by further using the collected data in an anonymized way, where only the general characteristics of the organization under consideration can be revealed. We will openly share the anonymized data derived from this study through the institutional data repository, including interview summaries. We will delete your personal data (i.e. your name and signature on the consent form and your e-mail address) within six months after data collection.

Your participation in this study is entirely voluntary and you can withdraw at any time. You are free to omit any questions.

This interview will take approximately 40 minutes to complete. We will be asking you 28 questions, starting with general questions describing the organization you belong to, and continuing with open-ended questions concerning the identified barriers towards adoption of Green Artificial Intelligence (Green AI), for your organization. The interview will end with some overall questions about the established policy framework in your country.

This study is being conducted as part of the postgraduate program "e-Government" of the Department of Information and Communication Systems Engineering, University of the Aegean, under the supervision of Associate Professor C. Alexopoulos.

The research aims to examine the current state of e-government in Greece and to identify the main problems and challenges that need to be addressed to achieve the objectives of e-government.

In case of questions, please contact the involved researchers:

Evangelia Alexopoulou – evangelia.alex@gmail.com

8. Informed consent

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
A: GENERAL AGREEMENT – RESEARCH GOALS, PARTICIPANT TASKS AND VOLUNTARY PARTICIPATION		
1. I have read and understood the study information dated [DD/MM/YYYY], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	☐	☐
2. I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions, and I can withdraw from the study at any time, without having to give a reason.	☐	☐
3. I understand that taking part in the study involves an audio-recorded interview, which is further transcribed, and once this is done, the audio recording will be destroyed.	☐	☐
4. I understand that the study will end after a sufficient number of interviews across different organizations, academia, the public sector, and industry in Greece have been conducted to refine the model with its further application. The expected end date of this interview study is March 2026.		
B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)		

«Towards Green AI adoption and policy for sustainable AI governance»

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
5. I understand that taking part in the study also involves collecting specific personally identifiable information (PII) (i.e., your name and signature on this consent form and your e-mail address if you decide to provide this to receive our study's results) and associated personally identifiable research data (PIRD) (i.e., your organization) with the potential risk of my identity being revealed.	☐	☐
6. I understand that the following steps will be taken to minimize the threat of a data breach and protect my identity in the event of such a breach by anonymizing the data and mostly using them in an aggregated manner. Audio records will be transcribed (only accessible to the study team), while audio recordings will be deleted after transcription. Transcriptions will be anonymized and stored locally and secured. We will only report about organizations where interviewees are employed in an aggregated way and quotes in our publications will be anonymized.	☐	☐
7. I understand that personal information collected about me that can identify me, such as my name will not be shared beyond the study team.	☐	☐
8. I understand that the (identifiable) personal data I provide will be destroyed by the end of the research.	☐	☐
C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION		
9. I understand that after the research study the de-identified information I provide will be used for reports, publications, websites, as well as the development of policies to improve the current state of the art of green AI adoption framework. In specific cases we expect to cite provided answers (anonymized quotes) to ensure accurate references to issues.	☐	☐
10. I agree that my responses, views or other input can be quoted anonymously in research outputs.	☐	☐

Signatures		
_____	_____	
Name of participant [printed]	Signature	Date

I, as researcher, have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Researcher name [printed]

Signature

Date

Study contact details for further information: [*Name, phone number, email address*]

Interview questions

Your organization

We will now start the interview with some questions about the organization you are working for.

Q1. By what government/private organization are you employed? (name, domain)
Q2. What are the main tasks of your organization?
Q3. What is your role in this organization?

Your organization: Green AI Strategy and Readiness

Many organizations today use Artificial Intelligence (AI) and are also trying to reduce their environmental impact. Green Artificial Intelligence (Green AI) refers to AI systems that are designed and used in an energy-efficient and environmentally responsible way. In the following questions, we focus on your organization's **strategy, readiness, resources, and preparedness** to adopt Green AI.

Q4. Has your organization adopted any Artificial Intelligence (AI) systems? → If yes, go to question 5 → If no, go to question 9
Q5. What were the main drivers behind AI adoption in your organization?
Q6. Is your organization familiar with the concept of Green AI?
Q7. Has your organization adopted or is planning to adopt Green AI solutions?
Q8. What motivates or discourages your organization from adopting Green AI?
Q9. What prevents your organization from adopting any Artificial Intelligence (AI) systems (if applicable)?

Barrier-related questions

We will now discuss various types of barriers related to the adoption of Green Artificial Intelligence (Green AI). We would like to understand whether and how these barriers are relevant for your organization. These barriers may be related to technical, organizational, economic, regulatory, or cultural aspects of Green AI adoption.

We will start by discussing **usage barriers**. Usage barriers refer to the degree to which adopting Green AI requires changes in your organization's **technical infrastructure, operational processes, data management practices, and daily routines**.

Q10. Are there any usage barriers related to changes in organizational routines that hinder Green AI adoption? (UBn)
- Lack of high-quality data for energy-efficient AI training (UB1)
- Complexity of preparing data for Green AI models (UB2)
- Complexity of designing energy-efficient AI systems (UB3)
- Complexity of deploying Green AI infrastructure (UB4)
- Lack of standardized Green AI implementation processes (UB5)
- Limited availability of Green AI tools and platforms (UB6)
- Limited automation for optimizing AI energy efficiency (UB7)
- High effort required to maintain Green AI systems (UB8)

- | |
|---|
| <p>Q11. Are there any other usage barriers that form a barrier for your organization to Green AI adoption? (UBn)</p> <p>Q12. How technologically ready is your organization to implement energy-efficient AI solutions?</p> |
|---|

We will now discuss **value barriers** related to the adoption of Green Artificial Intelligence (Green AI). We aim to understand whether and how these barriers are relevant for your organization. Value barriers refer to the extent to which the **perceived benefits of Green AI are considered lower than its costs or compared to alternative solutions**.

For example, organizations may perceive that Green AI does not always deliver sufficient operational, economic, or environmental value. There may be concerns regarding the **high costs of implementation, infrastructure, and training**, as well as uncertainty about the **return on investment and the measurable sustainability benefits**. In some cases, organizations invest significant resources in adopting Green AI, while the broader benefits may primarily benefit external stakeholders, such as citizens, customers, or society at large.

Q13. Are there any value barriers that hinder Green AI adoption? (VB)
- Green AI provides limited benefits for society (VB1)
- Green AI provides limited business value (VB2)
- Data quality limitations (VB3)
- Societal benefits lower than costs (VB4)
- Organizational benefits lower than costs (VB5)
- High investment and operational costs (VB6)
- No added value to operations (VB7)
- Resource requirements outweigh benefits (VB8)
- return on investment (ROI) of Green AI is unclear
Q14. Are there any other value barriers that form a barrier for your organization to Green AI adoption? (VBn)

We will now address the potential **risk barriers** associated with the development and deployment of Green AI and would like to understand whether and how these risks are relevant to your organization. Risk barriers refer to the perceived uncertainty regarding financial, functional, and social consequences of adopting Green AI solutions (e.g., unintended misuse, incorrect outputs or interpretations, data privacy concerns, errors in model development or deployment, data and model quality issues, energy efficiency trade-offs, etc.).

Q15. Are there any risk barriers that hinder Green AI adoption?
Q16. To what extent do the following situations form a barrier that hinder Green AI adoption in your organization:
- Malfunctioning or inefficient AI systems (RB1)
- Incorrect sustainability performance measurements (RB2)
- Low trust in Green AI outputs (RB3)
- Regulatory violations- Regulatory compliance requirements for Green AI are unclear (RB4)
- Sensitive data exposure - Green AI adoption involves significant data security and privacy risks (RB5)

- Implementation errors (RB6)
- Reputational damage (RB7)
- Competitive disadvantage (RB8)
- Competitors benefit more (RB9)
Q17. Are there any other risk barriers that form a barrier for your organization to Green AI adoption? What regulatory, financial or security risks hinder Green AI adoption (RBn)?

We will now turn to the discussion of **tradition-related barriers** to the adoption of Green AI and would like to understand whether and how these barriers are relevant to your organization. Tradition barriers refer to the extent to which the adoption of Green AI requires organizations or users to change established values, norms, routines, and ways of working.

Q18. Are there any tradition barriers related to the required changes in your organization's routines that form a challenge for the adoption of Green AI? (TBn)
Q19. To what extent do the following situations form a barrier to Green AI adoption of your organization:
- Existing IT systems are sufficient (TB1)
- Resistance to sustainability-driven transformation (TB2)
- Lack of Green AI skills (TB3)
- Lack of training (TB4)
- Resistance to changing operational processes (TB5)
Q20. Are there any other tradition barriers that form a barrier for your organization to adoption of Green AI? What cultural or skills-related barriers hinder Green AI adoption? (TBn)

We will now discuss **image-related barriers** to the adoption of Green AI and would like to understand whether and how they are relevant to your organization. Image barriers refer to the extent to which Green AI is perceived as having a potentially unfavorable image, for example due to concerns that poor model performance, low data quality, misleading outputs, or unintended negative consequences could harm the organization's reputation or lead to incorrect conclusions and public criticism.

Q21. Are there any image barriers related to the required changes in your organization's routines that form a challenge for adoption Green AI strategies? (IBn)
Q22. To what extent do the following situations form a barrier to Green AI adoption of your organization:
- Low practical relevance (IB1)
- Reputation damage risk (IB2)
- Credibility damage risk (IB3)
- Public criticism (IB4)
- your organization fears that associating them with incorrect conclusions drawn from OGD analysis by OGD users will damage its reputation. (IB5)
Q23. Are there any other image barriers (e.g. reputation-related barriers) that form a barrier for your organization? (IBn)
Q24. What internal or external barriers hinder your Green AI adoption efforts?
Q25. Do national or European policies influence your organization's decision to adopt Green AI?
Q26. What policy measures, actions or incentives would support Green AI adoption?

Q27. Are there any additional barriers or facilitators you would like to mention regarding Green AI adoption?

Q28. From your perspective, what are the key enablers for successful Green AI implementation?

Thank you for your participation in this study! We appreciate your time!

Appendix C – Interviews Question & Answers

All interviews were conducted in Greek, therefore, the documents (questions-answers) provided below are in Greek.

Interviewee No.1

Πλήρης Συνέντευξη – Συνδυασμός αυτούσιας (ελαφρώς καθαρισμένης) και επιμελημένης απόδοσης

Το παρόν Παράρτημα περιλαμβάνει την πλήρη παρουσίαση της ημι-δομημένης συνέντευξης που πραγματοποιήθηκε στο πλαίσιο της διπλωματικής εργασίας. Για κάθε μία από τις είκοσι οκτώ (28) ερωτήσεις παρατίθεται η αυτούσια απάντηση του συνεντευξιζόμενου σε ελαφρώς καθαρισμένη μορφή (με αφαίρεση λεκτικού θορύβου και επαναλήψεων), καθώς και η ακαδημαϊκά επιμελημένη απόδοσή της. Περιλαμβάνονται όλα τα υποερωτήματα και τα σχόλια που διατυπώθηκαν κατά τη ροή της συνέντευξης.

E1. Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;

Αυτούσια απάντηση (καθαρισμένη):

Εργάζομαι στην ΕΔΥΤΕ, το Εθνικό Δίκτυο Υποδομών Τεχνολογίας και Έρευνας, και απαντώ με αυτή την ιδιότητα.

Επιμελημένη ακαδημαϊκή απόδοση:

Ο συνεντευξιζόμενος εργάζεται στην ΕΔΥΤΕ (Εθνικό Δίκτυο Υποδομών Τεχνολογίας και Έρευνας).

E2. Ποια είναι τα βασικά καθήκοντα του οργανισμού σας;

Αυτούσια απάντηση (καθαρισμένη):

Η ΕΔΥΤΕ παρέχει υποδομές στην ερευνητική και ακαδημαϊκή κοινότητα, υποδομές δικτύωσης και υποστηρίζει το Υπουργείο Ψηφιακής Διακυβέρνησης στον ψηφιακό μετασχηματισμό.

Επιμελημένη ακαδημαϊκή απόδοση:

Η ΕΔΥΤΕ παρέχει υποδομές πληροφορικής και δικτύωσης και υποστηρίζει τον ψηφιακό μετασχηματισμό του δημόσιου τομέα.

E3. Ποιος είναι ο ρόλος σας στον οργανισμό;

Αυτούσια απάντηση (καθαρισμένη):

Είμαι Αναπληρωτής Διευθυντής στη Διεύθυνση Ψηφιακού Μετασχηματισμού και Ψηφιακών Ικανοτήτων και ασχολούμαι με τον σχεδιασμό και την υλοποίηση συστημάτων για τον δημόσιο τομέα.

Επιμελημένη ακαδημαϊκή απόδοση:

Ο συνεντευξιζόμενος κατέχει τη θέση του Αναπληρωτή Διευθυντή στη Διεύθυνση Ψηφιακού Μετασχηματισμού.

E4. Έχει υιοθετήσει ο οργανισμός σας συστήματα τεχνητής νοημοσύνης;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, ο οργανισμός έχει υιοθετήσει συστήματα τεχνητής νοημοσύνης.

Επιμελημένη ακαδημαϊκή απόδοση:

Ο οργανισμός αξιοποιεί ήδη συστήματα τεχνητής νοημοσύνης.

E5. Ποιοι ήταν οι κύριοι παράγοντες που οδήγησαν στην υιοθέτηση ΤΝ;

Αυτούσια απάντηση (καθαρισμένη):

Οι ανάγκες των δημόσιων φορέων και οι απαιτήσεις των ευρωπαϊκών χρηματοδοτικών εργαλείων.

Επιμελημένη ακαδημαϊκή απόδοση:

Η υιοθέτηση οφείλεται σε ανάγκες φορέων και σε απαιτήσεις ευρωπαϊκών προγραμμάτων.

E6. Είναι ο οργανισμός εξοικειωμένος με την πράσινη ΤΝ;

Αυτούσια απάντηση (καθαρισμένη):

Είναι εν μέρει εξοικειωμένος, αλλά όχι σε συστηματικό επίπεδο.

Επιμελημένη ακαδημαϊκή απόδοση:

Ο οργανισμός εμφανίζει μερική εξοικείωση με την πράσινη τεχνητή νοημοσύνη.

E7. Έχει υιοθετήσει ή σχεδιάζει λύσεις πράσινης ΤΝ;

Αυτούσια απάντηση (καθαρισμένη):

Δεν υπάρχουν υλοποιημένες λύσεις, αλλά υπάρχει προβληματισμός.

Επιμελημένη ακαδημαϊκή απόδοση:

Δεν έχουν υλοποιηθεί ακόμη λύσεις, αλλά υπάρχει μελλοντικός σχεδιασμός.

E8. Τι αποθαρρύνει την υιοθέτηση πράσινης ΤΝ;

Αυτούσια απάντηση (καθαρισμένη):

Η περιορισμένη γνώση του πεδίου και των διαθέσιμων λύσεων.

Επιμελημένη ακαδημαϊκή απόδοση:

Η περιορισμένη γνώση αποτελεί βασικό αποτρεπτικό παράγοντα.

E9. Πώς ορίζετε την πράσινη ΤΝ;

Αυτούσια απάντηση (καθαρισμένη):

Είναι ο σχεδιασμός συστημάτων ΤΝ που μεγιστοποιούν κοινωνική, οικονομική και περιβαλλοντική αξία με ελαχιστοποίηση των επιπτώσεων.

Επιμελημένη ακαδημαϊκή απόδοση:

Η πράσινη ΤΝ στοχεύει στη μεγιστοποίηση αξίας με ταυτόχρονη ελαχιστοποίηση περιβαλλοντικών επιπτώσεων.

E10. Υπάρχουν εμπόδια χρήσης;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, κυρίως σε δεδομένα, διαδικασίες και υποδομές.

Επιμελημένη ακαδημαϊκή απόδοση:

Υπάρχουν εμπόδια που σχετίζονται με δεδομένα και οργανωτικές διαδικασίες.

E11. Υπάρχουν άλλα εμπόδια χρήσης;

Αυτούσια απάντηση (καθαρισμένη):

Υπάρχει ανησυχία για πιθανή μείωση της ποιότητας των αποτελεσμάτων.

Επιμελημένη ακαδημαϊκή απόδοση:

Η ανησυχία για μειωμένη απόδοση αποτελεί πρόσθετο εμπόδιο.

E12. Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;

Αυτούσια απάντηση (καθαρισμένη):

Περίπου στο 50%, χωρίς συστηματικές μετρήσεις.

Επιμελημένη ακαδημαϊκή απόδοση:

Ο οργανισμός βρίσκεται σε μεσαίο επίπεδο τεχνολογικής ετοιμότητας.

E13. Υπάρχουν εμπόδια αξίας;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, κυρίως κόστος και αβεβαιότητα απόδοσης επένδυσης.

Επιμελημένη ακαδημαϊκή απόδοση:

Υπάρχουν εμπόδια αξίας που σχετίζονται με κόστος και ROI.

E14. Υπάρχουν άλλα εμπόδια αξίας;

Αυτούσια απάντηση (καθαρισμένη):

Όχι.

Επιμελημένη ακαδημαϊκή απόδοση:

Δεν αναφέρονται πρόσθετα εμπόδια αξίας.

E15. Υπάρχουν κίνδυνοι υιοθέτησης;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, κανονιστικοί και τεχνικοί.

Επιμελημένη ακαδημαϊκή απόδοση:

Υπάρχουν κανονιστικοί και τεχνικοί κίνδυνοι.

E16. Σε ποιο βαθμό υπάρχουν κίνδυνοι;

Αυτούσια απάντηση (καθαρισμένη):

Υπάρχουν σε κάποιο βαθμό.

Επιμελημένη ακαδημαϊκή απόδοση:

Οι κίνδυνοι αναγνωρίζονται σε μέτριο βαθμό.

E17. Υπάρχουν άλλοι κίνδυνοι;

Αυτούσια απάντηση (καθαρισμένη):

Όχι.

Επιμελημένη ακαδημαϊκή απόδοση:

Δεν αναφέρονται άλλοι κίνδυνοι.

E18. Υπάρχουν θεσμικά εμπόδια;

Αυτούσια απάντηση (καθαρισμένη):

Κανονισμοί και θέματα ιδιωτικότητας.

Επιμελημένη ακαδημαϊκή απόδοση:

Τα θεσμικά και κανονιστικά ζητήματα αποτελούν εμπόδιο.

E19. Υπάρχει αντίσταση στην αλλαγή;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, η αντίσταση στην αλλαγή είναι πρόβλημα.

Επιμελημένη ακαδημαϊκή απόδοση:

Η οργανωσιακή αντίσταση αποτελεί σημαντικό εμπόδιο.

E20. Υπάρχουν άλλα παραδοσιακά εμπόδια;

Αυτούσια απάντηση (καθαρισμένη):

Όχι.

Επιμελημένη ακαδημαϊκή απόδοση:

Δεν εντοπίζονται πρόσθετα παραδοσιακά εμπόδια.

E21. Υπάρχουν εμπόδια εικόνας;

Αυτούσια απάντηση (καθαρισμένη):

Υπάρχει φόβος για αρνητική εικόνα από κακή απόδοση.

Επιμελημένη ακαδημαϊκή απόδοση:

Υπάρχουν ανησυχίες για τη φήμη του οργανισμού.

E22. Υπάρχουν άλλα εμπόδια εικόνας;

Αυτούσια απάντηση (καθαρισμένη):

Τα ακούσια αρνητικά αποτελέσματα.

Επιμελημένη ακαδημαϊκή απόδοση:

Τα ακούσια αποτελέσματα αποτελούν πρόσθετο κίνδυνο.

E23. Επηρεάζει η ποιότητα δεδομένων την εικόνα;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, χαμηλή ποιότητα δεδομένων επηρεάζει την αξιοπιστία.

Επιμελημένη ακαδημαϊκή απόδοση:

Η ποιότητα δεδομένων είναι κρίσιμη για την εικόνα.

E24. Ποια εσωτερικά ή εξωτερικά εμπόδια υπάρχουν;

Αυτούσια απάντηση (καθαρισμένη):

Υπάρχει γενικός δισταγμός.

Επιμελημένη ακαδημαϊκή απόδοση:

Ο δισταγμός αποτελεί βασικό ανασταλτικό παράγοντα.

E25. Επηρεάζουν οι πολιτικές την υιοθέτηση;

Αυτούσια απάντηση (καθαρισμένη):

Ναι, εθνικές και ευρωπαϊκές πολιτικές.

Επιμελημένη ακαδημαϊκή απόδοση:

Οι πολιτικές επηρεάζουν σημαντικά την υιοθέτηση.

E26. Υπάρχουν επιπλέον παράγοντες;

Αυτούσια απάντηση (καθαρισμένη):

Η ανάγκη για ενημέρωση και εκπαίδευση.

Επιμελημένη ακαδημαϊκή απόδοση:

Η ενίσχυση ενημέρωσης και εκπαίδευσης είναι κρίσιμη.

E27. Τι θα διευκόλυνε την υιοθέτηση;

Αυτούσια απάντηση (καθαρισμένη):

Κίνητρα και υποστήριξη από την πολιτεία.

Επιμελημένη ακαδημαϊκή απόδοση:

Τα κίνητρα και η θεσμική υποστήριξη διευκολύνουν την υιοθέτηση.

E28. Ποιοι είναι οι βασικοί παράγοντες επιτυχίας;

Αυτούσια απάντηση (καθαρισμένη):

Υποδομές πειραματισμού και απτά παραδείγματα.

Επιμελημένη ακαδημαϊκή απόδοση:

Οι υποδομές και τα μετρήσιμα παραδείγματα είναι καθοριστικά.

Interviewee No.2

Αναλυτική Παρουσίαση Συνέντευξης – Ερωτήσεις, Υποερωτήματα και Απαντήσεις

Το παρόν Παράρτημα περιλαμβάνει την πλήρη και αναλυτική παρουσίαση της συνέντευξης, με σαφή διαχωρισμό κύριων ερωτήσεων (Ε), υποερωτημάτων (Εx.γ

όπου υπάρχουν) και απαντήσεων (Α). Οι απαντήσεις αποδίδονται σε ελαφρώς καθαρισμένη μορφή, χωρίς αλλοίωση του νοήματος, και είναι κατάλληλες για αυτούσια ένταξη σε διπλωματική εργασία.

E1. Σε ποιον ιδιωτικό ή κυβερνητικό οργανισμό εργάζεστε ή με τι ασχολείστε επαγγελματικά;

Ο συνεντευξιζόμενος εργάζεται ως εξωτερικός συνεργάτης της ΕΔΙΤΕ και συντονίζει δράσεις του Κόμβου Ψηφιακής Καινοτομίας, με έμφαση στον ψηφιακό μετασχηματισμό και την αξιοποίηση της τεχνητής νοημοσύνης στον δημόσιο τομέα.

E2. Ποιος είναι ο βασικός στόχος του Κόμβου Ψηφιακής Καινοτομίας;

Ο στόχος είναι η επιτάχυνση της υιοθέτησης της τεχνητής νοημοσύνης στον δημόσιο τομέα, μέσω μεταφοράς τεχνολογίας, τεχνογνωσίας και ανάπτυξης επιτυχημένων περιπτώσεων χρήσης.

E3. Ποια είναι η εμπειρία της ΕΔΙΤΕ σε πράσινες υποδομές;

Η ΕΔΙΤΕ έχει αναπτύξει πράσινα data centers και τον υπερυπολογιστή ΔΕΔΑΛΟ, αποτελώντας βασικό πυλώνα πράσινης υπολογιστικής στην Ελλάδα.

E4. Έχει υιοθετήσει ο οργανισμός σας συστήματα τεχνητής νοημοσύνης;

Ναι, η ΕΔΙΤΕ αναπτύσσει και υποστηρίζει συστήματα τεχνητής νοημοσύνης σε εθνικό επίπεδο.

E5. Ποιοι ήταν οι κύριοι παράγοντες που οδήγησαν στην υιοθέτηση της τεχνητής νοημοσύνης;

Οι κύριοι παράγοντες ήταν η επιστημονική εμπειρία, η διαθεσιμότητα υποδομών και οι κοινωνικές και οικονομικές ανάγκες.

E6. Είναι οι φορείς εξοικειωμένοι με την πράσινη τεχνητή νοημοσύνη;

Η ΕΔΙΤΕ είναι ιδιαίτερα εξοικειωμένη, ενώ οι συνεργαζόμενοι φορείς βρίσκονται σε διαφορετικά επίπεδα ωριμότητας.

E7. Έχει υιοθετηθεί ή σχεδιάζεται υιοθέτηση πράσινης ΤΝ;

Ο οργανισμός κινείται ξεκάθαρα προς την υιοθέτηση λύσεων πράσινης τεχνητής νοημοσύνης.

E8. Τι αποθαρρύνει ή παρακινεί την υιοθέτηση πράσινης ΤΝ;

Αποτρεπτικοί παράγοντες είναι οι περιορισμένοι πόροι, ενώ παρακινητικοί η ανάπτυξη δεξιοτήτων και η μεταφορά τεχνογνωσίας.

E9. Υπάρχουν οργανωσιακά εμπόδια και θέματα δεδομένων;

Ναι, χαμηλή ψηφιακή ωριμότητα, ανάγκη απλοποίησης διαδικασιών και έλλειψη ποιοτικών δεδομένων.

E10. Αποτελεί εμπόδιο η ποιότητα των δεδομένων;

Ναι, αποτελεί κρίσιμο εμπόδιο.

E11. Είναι εμπόδιο η πολυπλοκότητα σχεδιασμού και υποδομών;

Ναι, τόσο ο σχεδιασμός όσο και οι υποδομές αποτελούν σημαντικές προκλήσεις.

E12. Υπάρχει έλλειψη τυποποιημένων διαδικασιών;

Σε κάποιο βαθμό, αν και οι διαδικασίες προσεγγίζουν αυτές των παραδοσιακών συστημάτων.

E13. Απαιτείται αυξημένη συντήρηση;

Ναι, τα βελτιστοποιημένα συστήματα απαιτούν συνεχή παρακολούθηση.

E14. Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;

Ο οργανισμός θεωρείται ιδιαίτερα ώριμος τεχνολογικά.

E15. Υπάρχουν εμπόδια αξίας (κόστος, ROI);

Το υψηλό κόστος και η αβεβαιότητα απόδοσης επένδυσης αποτελούν βασικά εμπόδια.

E16. Είναι σαφές το κανονιστικό πλαίσιο;

Το κανονιστικό πλαίσιο εξελίσσεται με έντονη ευρωπαϊκή παρέμβαση.

E17. Υπάρχουν κίνδυνοι ασφάλειας και ιδιωτικότητας;

Οι κίνδυνοι αφορούν την ΤΝ γενικότερα και αντιμετωπίζονται με υπεύθυνες πρακτικές.

E18. Υπάρχουν εμπόδια δεξιοτήτων και αντίστασης στην αλλαγή;

Ναι, έλλειψη δεξιοτήτων και αντίσταση σε αλλαγές διαδικασιών.

E19. Πώς επηρεάζεται η εικόνα του οργανισμού;

Η πράσινη ΤΝ ενισχύει τη φήμη, ενώ η απουσία της μπορεί να δημιουργήσει κινδύνους.

E20. Ποια μέτρα πολιτικής θα ενίσχυαν την υιοθέτηση;

Περιβαλλοντικά κριτήρια, μελέτες βιωσιμότητας και θεσμικά κίνητρα.

E21. Ποιοι είναι οι βασικοί παράγοντες επιτυχίας;

Στρατηγική καθοδήγηση, ενσωμάτωση στην ψηφιακή πολιτική και ενημέρωση φορέων.

E22. Υπάρχει ανάγκη πειραματισμού;

Ναι, απαιτούνται πιλοτικά έργα και sandbox περιβάλλοντα.

E23. Ποιος ο ρόλος της εκπαίδευσης;

Η εκπαίδευση θεωρείται κρίσιμη για βιώσιμη υιοθέτηση.

E24. Ποιος ο ρόλος της πολιτείας;

Η πολιτεία πρέπει να θέτει σαφή κατεύθυνση και κίνητρα.

E25. Υπάρχουν κοινωνικές επιπτώσεις;

Ναι, η πράσινη ΤΝ συνδέεται με κοινωνική υπευθυνότητα.

E26. Πώς συνδέεται με την καινοτομία;

Η πράσινη ΤΝ αποτελεί μοχλό βιώσιμης καινοτομίας.

E27. Ποια είναι τα βασικά ρίσκα μη υιοθέτησης;

Η απώλεια ανταγωνιστικότητας και αξιοπιστίας.

E28. Τελικό συμπέρασμα για την πράσινη ΤΝ;

Η πράσινη τεχνητή νοημοσύνη αποτελεί αναγκαία στρατηγική επιλογή για τον δημόσιο τομέα.

Interviewee No.3

E1. Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε (όνομα και τομέας);

A: Ονομάζομαι ΜΔ και εργάζομαι ως μεταδιδασκτορική ερευνήτρια στο Ινστιτούτο Πληροφορικής και Τηλεπικοινωνιών του ΕΚΕΦΕ «Δημόκριτος».

E2. Ποια είναι τα κύρια καθήκοντα του οργανισμού σας;

A: Ο οργανισμός έχει ως βασική αποστολή την έρευνα, την ανάπτυξη και την καινοτομία. Πρόκειται για έναν πολυθεματικό ερευνητικό οργανισμό, στον οποίο η τεχνητή νοημοσύνη εφαρμόζεται πλέον σε πολλά επιστημονικά πεδία.

E3. Ποιος είναι ο ρόλος σας στον φορέα;

A: Ο ρόλος μου είναι αυτός της μεταδιδασκτορικής ερευνήτριας, με ερευνητική

ενασχόληση στην αξιόπιστη, ηθική και κανονιστικά συμμορφούμενη τεχνητή νοημοσύνη.

E4. Έχει υιοθετήσει ο οργανισμός συστήματα τεχνητής νοημοσύνης;

A: Σε λειτουργικό και διοικητικό επίπεδο δεν είναι σαφές αν έχουν υιοθετηθεί πλήρως συστήματα τεχνητής νοημοσύνης. Ωστόσο, σε ερευνητικό επίπεδο αναπτύσσονται εκτεταμένα συστήματα τεχνητής νοημοσύνης, πολλά εκ των οποίων οδηγούν και σε εμπορικά προϊόντα.

E5. Είναι ο οργανισμός εξοικειωμένος με την έννοια της πράσινης τεχνητής νοημοσύνης;

A: Υπάρχει εξοικείωση κυρίως μέσω ερευνητικών έργων που σχετίζονται με έξυπνες υποδομές, ενεργειακή αποδοτικότητα και βιώσιμες τεχνολογικές λύσεις.

E6. Σχεδιάζει ο οργανισμός την υιοθέτηση λύσεων πράσινης τεχνητής νοημοσύνης;

A: Ναι, τόσο μέσω της ανάπτυξης εφαρμογών όσο και στον σχεδιασμό συστημάτων, με έμφαση στη μείωση του περιβαλλοντικού αποτυπώματος.

E7. Ποιοι παράγοντες παρακινούν ή αποθαρρύνουν την υιοθέτηση πράσινης τεχνητής νοημοσύνης;

A: Το βασικό κίνητρο είναι η πρωτοπορία και το πρακτικό όφελος. Δεν υπάρχουν έντονοι αποτρεπτικοί παράγοντες, αλλά υφίστανται εμπόδια όπως η έλλειψη δεδομένων και υποδομών.

E8. Υπάρχουν εμπόδια χρήσης που σχετίζονται με οργανωτικές αλλαγές;

A: Ναι, κυρίως λόγω της ανάγκης προσαρμογής διαδικασιών και υποδομών.

E9. Η έλλειψη υψηλής ποιότητας δεδομένων αποτελεί εμπόδιο;

A: Ναι, αποτελεί σοβαρό εμπόδιο, καθώς χωρίς αξιόπιστα δεδομένα δεν μπορούν να εφαρμοστούν ενεργειακά αποδοτικά συστήματα.

E10. Η ανάγκη αναβάθμισης υποδομών αποτελεί εμπόδιο;

A: Ναι, η αναβάθμιση κτιριακών και τεχνολογικών υποδομών απαιτεί σημαντικές επενδύσεις.

E11. Υπάρχουν εμπόδια αξίας που σχετίζονται με το κόστος και τα οφέλη;

A: Υπάρχει αβεβαιότητα ως προς το αν τα οφέλη υπερβαίνουν το κόστος, τόσο για τον οργανισμό όσο και για την κοινωνία.

E12. Το υψηλό κόστος επένδυσης και λειτουργίας αποτελεί εμπόδιο;

A: Ναι, απαιτούνται σημαντικοί οικονομικοί και ανθρώπινοι πόροι.

E13. Υπάρχουν κίνδυνοι που δυσχεραίνουν την υιοθέτηση της πράσινης τεχνητής νοημοσύνης;

A: Ναι, σχετίζονται με την αβεβαιότητα, τη μέτρηση βιωσιμότητας και την εμπιστοσύνη στα αποτελέσματα.

E13α. Η δυσλειτουργία συστημάτων αποτελεί κίνδυνο;

A: Ναι, αν τα συστήματα δεν είναι αξιόπιστα, υπονομεύεται η υιοθέτηση.

E13β. Η ανακριβής μέτρηση βιωσιμότητας αποτελεί κίνδυνο;

A: Ναι, καθώς η βιωσιμότητα δεν ορίζεται πάντα με σαφήνεια.

E13γ. Η χαμηλή εμπιστοσύνη στα αποτελέσματα αποτελεί εμπόδιο;

A: Ναι, επηρεάζει τη διάθεση υιοθέτησης.

E13δ. Η ασάφεια κανονιστικής συμμόρφωσης αποτελεί εμπόδιο;

A: Ναι, καθώς τα κανονιστικά πλαίσια είναι σύνθετα και δύσκολα εφαρμόσιμα.

E13ε. Υπάρχουν κίνδυνοι για την ιδιωτικότητα και την ασφάλεια δεδομένων;

A: Όχι περισσότεροι από άλλες εφαρμογές τεχνητής νοημοσύνης.

- E13στ. Τα σφάλματα υλοποίησης αποτελούν εμπόδιο;
Α: Ναι, στον ίδιο βαθμό που ισχύει για κάθε σύστημα τεχνητής νοημοσύνης.
- E13ζ. Υπάρχει κίνδυνος βλάβης της φήμης του οργανισμού;
Α: Όχι ως εμπόδιο, αλλά ως κίνητρο για υπεύθυνο σχεδιασμό.
- E13η. Υπάρχει ανταγωνιστικό μειονέκτημα;
Α: Εξαρτάται από τον τομέα δραστηριότητας.
- E14. Υπάρχουν παραδοσιακά ή πολιτισμικά εμπόδια;
Α: Ναι, κυρίως λόγω έλλειψης ενημέρωσης και κουλτούρας βιωσιμότητας.
- E15. Η αντίσταση στην αλλαγή αποτελεί εμπόδιο;
Α: Ναι, ιδιαίτερα όταν δεν υπάρχει κοινή κατανόηση της βιωσιμότητας.
- E16. Υπάρχουν κίνδυνοι για τη φήμη και την αξιοπιστία;
Α: Η δημόσια κριτική δεν αποτελεί εμπόδιο αλλά αναμενόμενο στοιχείο.
- E17. Υπάρχουν άλλοι κανονιστικοί ή οικονομικοί κίνδυνοι;
Α: Τα βασικά έχουν ήδη καλυφθεί.
- E18. Ποια εσωτερικά εμπόδια παρεμποδίζουν την υιοθέτηση;
Α: Η έλλειψη ολιστικής ενημέρωσης και η ποικιλομορφία απόψεων.
- E19. Υπάρχουν εξωτερικά εμπόδια;
Α: Όχι πέραν του γενικού θεσμικού πλαισίου.
- E20. Επηρεάζουν οι εθνικές και ευρωπαϊκές πολιτικές την υιοθέτηση;
Α: Ναι, σε σημαντικό βαθμό.
- E21. Ποια μέτρα πολιτικής θα ενίσχυαν την υιοθέτηση;
Α: Μέτρα με ουσιαστικό αντίκτυπο στην καθημερινότητα των εργαζομένων.
- E22. Υπάρχει εννοιολογική ασάφεια στον όρο Green AI;
Α: Ναι, συχνά συγχέεται η χρήση AI για περιβαλλοντικούς σκοπούς με τον περιβαλλοντικό της αντίκτυπο.
- E23. Υπάρχει κίνδυνος παραπλανητικών συμπερασμάτων;
Α: Όχι για τον οργανισμό, λόγω υψηλής τεχνογνωσίας.
- E24. Ποια είναι τα βασικά οργανωτικά εμπόδια;
Α: Η έλλειψη κοινής κατανόησης του προβλήματος.
- E25. Υπάρχουν εξωτερικοί παράγοντες που επηρεάζουν;
Α: Μόνο το ευρύτερο θεσμικό περιβάλλον.
- E26. Ποια πολιτικά ή θεσμικά μέτρα θα ενίσχυαν την υιοθέτηση;
Α: Ουσιαστικά κίνητρα και όχι μόνο επικοινωνιακές δράσεις.
- E27. Υπάρχουν άλλες κρίσιμες παρατηρήσεις;
Α: Πρέπει να διαχωρίζεται σαφώς ο ρόλος της AI ως εργαλείο και ως πηγή περιβαλλοντικού κόστους.
- E28. Ποιοι είναι οι βασικοί παράγοντες επιτυχούς εφαρμογής της πράσινης τεχνητής νοημοσύνης;
Α: Η ενημέρωση, η εκπαίδευση και η ενεργή συμμετοχή της κοινωνίας.

Interviewee No.4

1. (Ε.) Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;
(Α.) Ο ερωτώμενος εργάζεται στο Χαροκόπειο Πανεπιστήμιο.
2. (Ε.) Ποια είναι τα κύρια καθήκοντα του οργανισμού σας;

(Α.) Τα κύρια καθήκοντα του οργανισμού είναι η παροχή εκπαίδευσης και η διεξαγωγή επιστημονικής έρευνας.

3. (Ε.) Ποιος είναι ο ρόλος σας στον οργανισμό (βαθμίδα ή θέση);

(Α.) Ο ερωτώμενος είναι Αναπληρωτής Καθηγητής στο Τμήμα Πληροφορικής και Τηλεματικής με γνωστικό αντικείμενο την Τεχνητή Νοημοσύνη και τη Μηχανική Μάθηση.

4. (Ε.) Έχει υιοθετήσει ο οργανισμός σας συστήματα Τεχνητής Νοημοσύνης;

(Α.) Ο οργανισμός έχει υιοθετήσει συστήματα ΤΝ κυρίως σε ερευνητικό επίπεδο. Σε επίπεδο διοικητικής λειτουργίας, η χρήση της ΤΝ παραμένει σε πειραματικό στάδιο (π.χ. δοκιμαστικά chatbots), με περιορισμένη διάρκεια/κλίμακα λόγω κόστους.

5. (Ε.) Ποιοι ήταν οι κύριοι παράγοντες που οδήγησαν στην υιοθέτηση της ΤΝ;

(Α.) Βασικός παράγοντας ήταν η ερευνητική δραστηριότητα. Δευτερευόντως, αξιοποιήθηκαν πιλοτικά εφαρμογές για υποστήριξη φοιτητών και ακαδημαϊκών διαδικασιών (π.χ. έλεγχος λογοκλοπής/AI περιεχομένου).

6. (Ε.) Είναι ο οργανισμός σας εξοικειωμένος με την έννοια της Πράσινης ΤΝ;

(Α.) Υπάρχει θεωρητική εξοικείωση, ωστόσο επισημαίνεται ότι τα σύγχρονα συστήματα ΤΝ είναι ιδιαίτερα ενεργοβόρα και η μείωση της κατανάλωσης αποτελεί ακόμη τεχνική/ερευνητική πρόκληση.

7. (Ε.) Υιοθετούνται πρακτικές Πράσινης ΤΝ σε επίπεδο υποδομών;

(Α.) Σε επίπεδο ερευνητικών υποδομών γίνεται προσπάθεια αποδοτικής χρήσης πόρων μέσω συστημάτων διαχείρισης εργασιών/προτεραιοποίησης (π.χ. SLURM) για βέλτιστη αξιοποίηση υπολογιστικών πόρων (GPU κ.λπ.) και αποφυγή άσκοπης κατανάλωσης.

8. (Ε.) Τι παρακινεί ή αποθαρρύνει την υιοθέτηση Πράσινης ΤΝ;

(Α.) Κύρια κίνητρα είναι το κόστος ενέργειας και η περιβαλλοντική ευαισθησία. Υπάρχει κουλτούρα βιώσιμης ανάπτυξης και πρακτικές παρακολούθησης κατανάλωσης (αισθητήρες, dashboards σε πραγματικό χρόνο).

9. (Ε.) Εμπόδια χρήσης: Σε ποιο βαθμό οι ακόλουθες καταστάσεις αποτελούν εμπόδια για την υιοθέτηση πρακτικών Πράσινης ΤΝ;

(Σημείωση: Οι απαντήσεις δίνονται με σύντομη αξιολόγηση και, όπου υπάρχει, σχόλιο.)

9.1 (Ε.) Έλλειψη υψηλής ποιότητας δεδομένων για την ενεργειακά αποδοτική εκπαίδευση συστημάτων ΤΝ.

(Α.) Ναι· θεωρείται σημαντικό εμπόδιο. Επισημαίνεται ότι συχνά χρησιμοποιούνται πολύ μεγάλα datasets που αυξάνουν τους απαιτούμενους υπολογιστικούς κύκλους. Αναφέρεται και σχετική ερευνητική κατεύθυνση (dataset condensation) για αποδοτικότερη αναπαράσταση.

9.2 (Ε.) Πολυπλοκότητα της προετοιμασίας δεδομένων για τα μοντέλα Πράσινης ΤΝ.

(Α.) Ναι· αποτελεί μεγάλο πρόβλημα, καθώς απαιτεί υπολογιστικούς πόρους και σημαντικό αποθηκευτικό χώρο.

- 9.3 (Ε.) Πολυπλοκότητα του σχεδιασμού ενεργειακά αποδοτικών συστημάτων ΤΝ.
(Α.) Ναι· σχετίζεται με τις τεχνικές προκλήσεις και το γεγονός ότι δεν υπάρχουν ακόμη καθιερωμένες λύσεις για υψηλή απόδοση με χαμηλή κατανάλωση στα μεγάλα μοντέλα.
- 9.4 (Ε.) Πολυπλοκότητα ανάπτυξης υποδομής Πράσινης ΤΝ.
(Α.) Ναι· ευθυγραμμίζεται με την προηγούμενη διάσταση, καθώς απαιτούνται σύνθετες υποδομές και κατάλληλος σχεδιασμός.
- 9.5 (Ε.) Έλλειψη τυποποιημένων διαδικασιών υλοποίησης Πράσινης ΤΝ.
(Α.) Ναι· αναφέρεται απουσία guidelines και τονίζεται ότι το πεδίο είναι δυναμικό, άρα οι “καλές πρακτικές” μεταβάλλονται γρήγορα.
- 9.6 (Ε.) Περιορισμένη διαθεσιμότητα εργαλείων και πλατφορμών Πράσινης ΤΝ.
(Α.) Ναι· σημειώνεται έλλειψη διαθέσιμων εργαλείων.
- 9.7 (Ε.) Περιορισμένη αυτοματοποίηση για τη βελτιστοποίηση της ενεργειακής αποδοτικότητας της ΤΝ.
(Α.) Ναι· θεωρείται εμπόδιο. Επισημαίνεται ότι πριν από την αυτοματοποίηση απαιτείται πρώτα ωρίμανση/τεκμηρίωση των τεχνικών λύσεων.
- 9.8 (Ε.) Απαιτείται μεγάλη προσπάθεια για τη συντήρηση συστημάτων Πράσινης ΤΝ.
(Α.) Ναι· η συντήρηση συστημάτων ΤΝ είναι γενικά απαιτητική και επιπλέον περιορισμοί (monitoring, εξοικονόμηση ενέργειας) αυξάνουν τη συνθετότητα.
- 9.9 (Ε.) Υπάρχουν άλλα εμπόδια χρήσης που αποτελούν φραγμό για την υιοθέτηση Πράσινης ΤΝ;
(Α.) Δεν αναφέρθηκαν επιπλέον εμπόδια πέραν των παραπάνω.
10. (Ε.) Πόσο τεχνολογικά έτοιμος είναι ο οργανισμός σας για ενεργειακά αποδοτικές λύσεις ΤΝ;
(Α.) Δεν είναι πλήρως έτοιμος· υπάρχει monitoring, αλλά δεν έχουν εγκατασταθεί συστήματα αυτοματοποιημένης δράσης (actuation) βάσει feedback.
11. (Ε.) (Εμπόδια αξίας) Η Πράσινη ΤΝ προσφέρει περιορισμένα ωφέλη για την κοινωνία;
(Α.) Στο πλαίσιο του οργανισμού δεν τίθεται ως κύριο εμπόδιο, καθώς τα KPIs είναι εκπαιδευτικά/ερευνητικά και η χρήση ΤΝ θεωρείται δικαιολογημένη.
12. (Ε.) Η Πράσινη ΤΝ προσφέρει περιορισμένη επιχειρηματική αξία;
(Α.) Δεν εξετάζεται άμεσα από τον οργανισμό, αν και σε συνεργασίες/έργα μπορεί να υπάρχει αβεβαιότητα για το άμεσο όφελος, με προσδοκία μελλοντικής αξίας.
13. (Ε.) Οι περιορισμοί στην ποιότητα δεδομένων αποτελούν εμπόδιο;
(Α.) Ναι· χαρακτηρίζεται μεγάλο πρόβλημα και επισημαίνεται η έμφαση της αγοράς/έρευνας στη δημιουργία datasets.
14. (Ε.) Υπάρχουν κίνδυνοι που δυσχεραίνουν την υιοθέτηση Πράσινης ΤΝ;
(Α.) Ναι· αναφέρονται κίνδυνοι που σχετίζονται με ΤΝ γενικότερα: περιορισμένη γενίκευση, μεροληψίες (biases), ζητήματα ερμηνευσιμότητας και κίνδυνοι λανθασμένης χρήσης.

15. (Ε.) Σε ποιο βαθμό οι ακόλουθες καταστάσεις αποτελούν εμπόδια/κινδύνους (ενδεικτικά: δυσλειτουργία, ανακριβής μέτρηση βιωσιμότητας, χαμηλή εμπιστοσύνη, κανονιστική ασάφεια, έκθεση δεδομένων, σφάλματα υλοποίησης, ανταγωνιστικό μειονέκτημα);
(Α.) Αναγνωρίζονται ως σημαντικά, ιδίως: (α) δυσκολία εμπιστοσύνης/επίδοσης, (β) απουσία μεθοδολογίας μέτρησης βιωσιμότητας, (γ) κανονιστική ασάφεια (AI Act και έλλειψη πλαισίου για ενεργειακή απόδοση), (δ) ζητήματα προστασίας δεδομένων και (ε) ανάγκη αξιολόγησης trade-offs επίδοσης–κατανάλωσης.
16. (Ε.) Υπάρχουν επιπλέον κανονιστικοί/οικονομικοί/ασφαλιστικοί κίνδυνοι πέραν των ανωτέρω;
(Α.) Δεν προστέθηκαν επιπλέον.
17. (Ε.) Υπάρχουν εμπόδια εικόνας/φήμης που σχετίζονται με την υιοθέτηση Πράσινης ΤΝ;
(Α.) Ναι, κυρίως εάν συστήματα που παρέχουν υπηρεσίες (π.χ. προς φοιτητές ή προς την κοινωνία μέσω έργων) έχουν κακή επίδοση, θα μπορούσαν να δημιουργήσουν αρνητική εικόνα.
18. (Ε.) Υπάρχουν παραδοσιακά/πολιτισμικά εμπόδια που σχετίζονται με απαιτούμενες αλλαγές στις πρακτικές του οργανισμού;
(Α.) Ναι· στο διοικητικό/λειτουργικό σκέλος απαιτείται εκπαίδευση προσωπικού και απόκτηση δεξιοτήτων. Στο εκπαιδευτικό σκέλος, το εμπόδιο αφορά κυρίως την προσαρμογή προγραμμάτων σπουδών.
19. (Ε.) Σε ποιο βαθμό τα υπάρχοντα συστήματα ΤΝ είναι επαρκή;
(Α.) Δεν αξιολογούνται ως επαρκή για πλήρη υιοθέτηση σε λειτουργικό επίπεδο.
20. (Ε.) Αντίσταση στην αλλαγή που επιβάλλει η βιωσιμότητα (περιβαλλοντική/κοινωνική/οικονομική);
(Α.) Ναι· θεωρείται μεγάλο πρόβλημα, αντίστοιχο με την αντίσταση σε κάθε τεχνολογική αλλαγή.
21. (Ε.) Έλλειψη δεξιοτήτων/εκπαίδευσης για Πράσινη ΤΝ;
(Α.) Ναι· συνδέεται άμεσα με την ανάγκη εκπαίδευσης προσωπικού.
22. (Ε.) Κίνδυνος βλάβης φήμης/αξιοπιστίας/δημόσιας κριτικής;
(Α.) Ο κίνδυνος αξιοπιστίας σε συνεργασίες θεωρείται σημαντικός· ο κίνδυνος δημόσιας κριτικής αναφέρεται ως πιθανός αλλά όχι κεντρικός.
23. (Ε.) Υπάρχουν άλλα εμπόδια πέραν των ανωτέρω;
(Α.) Το οικονομικό κόστος παραμένει βασικό εμπόδιο· οι προϋπολογισμοί συχνά δεν επαρκούν για εκτεταμένο μετασχηματισμό.
24. (Ε.) Ποια εσωτερικά ή εξωτερικά εμπόδια παρεμποδίζουν τις προσπάθειες υιοθέτησης;

(Α.) Οικονομικοί περιορισμοί και χρονικοί περιορισμοί (φόρτος υποχρεώσεων, χρονοβόρος μετασχηματισμός).

25. (Ε.) Οι εθνικές ή ευρωπαϊκές πολιτικές επηρεάζουν την απόφαση υιοθέτησης Πράσινης ΤΝ;

(Α.) Ναι· η ύπαρξη ή πιθανή θέσπιση κανονιστικού πλαισίου στο μέλλον επηρεάζει τον οργανισμό.

26. (Ε.) Ποια μέτρα πολιτικής δράσης ή κίνητρα θα υποστήριζαν την υιοθέτηση Πράσινης ΤΝ;

(Α.) Προτείνονται παραδείγματα υλοποίησης, μορφές πιστοποίησης και προϋποθέσεις ενεργειακής απόδοσης/βιωσιμότητας σε ενισχύσεις και χρηματοδοτικά προγράμματα.

27. (Ε.) Υπάρχουν επιπλέον εμπόδια ή παράγοντες σχετικά με την υιοθέτηση Πράσινης ΤΝ;

(Α.) Τονίζεται η ραγδαία εξέλιξη και η έλλειψη ώριμων, καθιερωμένων λύσεων (σε hardware, δεδομένα, μεθοδολογίες, αρχιτεκτονικές). Επίσης, αναφέρεται ανάγκη ύπαρξης step-by-step οδηγιών για οργανισμούς.

28. (Ε.) Από τη δική σας οπτική, ποιοι είναι οι βασικοί παράγοντες για την επιτυχή εφαρμογή της Πράσινης ΤΝ;

(Α.) Καθοριστικοί παράγοντες θεωρούνται: (α) ωρίμανση/καθιέρωση τεχνολογιών και βέλτιστων πρακτικών ανά “component” και (β) ύπαρξη σαφών, βηματικών οδηγιών εφαρμογής για οργανισμούς. Επιπλέον σημειώνεται η ανάγκη τεκμηριωμένων αποτελεσμάτων ώστε οι φορείς να υιοθετούν πρακτικές ως μη early adopters.

Interviewee No.5

1. (Ε.) Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;

(Α.) Ο ερωτώμενος εργάζεται σε ιδιωτικό οργανισμό. Η εταιρεία ονομάζεται Indigital.

2. (Ε.) Ποια είναι τα κύρια καθήκοντα του οργανισμού / της εταιρείας;

(Α.) Εταιρεία πληροφορικής με δραστηριότητα σε πληροφοριακά συστήματα, υπηρεσίες πληροφορικής, ψηφιοποίηση, ανάπτυξη εφαρμογών, τεχνητή νοημοσύνη και έργα δημόσιου και ιδιωτικού τομέα.

3. (Ε.) Ποιος είναι ο ρόλος σας στον οργανισμό;

(Α.) Ο ερωτώμενος διευθύνει τον τομέα Τεχνητής Νοημοσύνης και Έρευνας.

4. (Ε.) Έχει υιοθετήσει ο οργανισμός σας συστήματα Τεχνητής Νοημοσύνης;

(Α.) Ναι.

5. (Ε.) Ποιοι ήταν οι κύριοι παράγοντες που οδήγησαν στην υιοθέτηση ΤΝ;

(Α.) Η ανάγκη της αγοράς και το οικονομικό σκέλος.

6. (Ε.) Είναι ο οργανισμός σας εξοικειωμένος με την έννοια της Πράσινης ΤΝ;

(Α.) Όχι ιδιαίτερα, μόνο σε γενικό επίπεδο.

7. (Ε.) Έχει υιοθετήσει ή σχεδιάζει να υιοθετήσει λύσεις Πράσινης ΤΝ;
(Α.) Δεν έχει συζητηθεί επίσημα, εφαρμόζονται όμως έμμεσα μικρότερα μοντέλα λόγω κόστους.
8. (Ε.) Τι παρακινεί ή αποθαρρύνει την υιοθέτηση Πράσινης ΤΝ;
(Α.) Το κόστος, κυρίως για τον πελάτη και τις υποδομές.
9. (Ε.) Εμπόδια χρήσης Πράσινης ΤΝ:
9.1 Έλλειψη ποιοτικών δεδομένων – Ναι, ειδικά λόγω προσωπικών δεδομένων.
9.2 Πολυπλοκότητα προετοιμασίας δεδομένων – Όχι, καλύπτεται in-house.
9.3 Πολυπλοκότητα σχεδιασμού συστημάτων – Όχι ιδιαίτερα.
9.4 Πολυπλοκότητα υποδομής – Όχι, ανατίθεται σε τρίτους.
9.5 Έλλειψη τυποποιημένων διαδικασιών – Ναι.
9.6 Περιορισμένα εργαλεία – Όχι.
9.7 Περιορισμένη αυτοματοποίηση – Ναι.
9.8 Συντήρηση συστημάτων – Έμμεσα ναι.
10. (Ε.) Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;
(Α.) Όχι ιδιαίτερα έτοιμος να εντοπίσει, αλλά έτοιμος να εφαρμόσει.
11. (Ε.) Περιορισμένα κοινωνικά ωφέλη;
(Α.) Όχι.
12. (Ε.) Περιορισμένη επιχειρηματική αξία;
(Α.) Όχι.
13. (Ε.) Περιορισμοί ποιότητας δεδομένων;
(Α.) Ναι.
14. (Ε.) Υπάρχουν κίνδυνοι υιοθέτησης;
(Α.) Ναι.
15. (Ε.) Κίνδυνοι (δυσλειτουργία, ανακριβείς μετρήσεις, εμπιστοσύνη, κανονισμοί, φήμη, ανταγωνισμός);
(Α.) Ναι σε όλα.
16. (Ε.) Άλλοι κανονιστικοί/οικονομικοί κίνδυνοι;
(Α.) Οικονομικοί και εξάρτηση από συνεργάτες.
17. (Ε.) Παραδοσιακά εμπόδια;
(Α.) Αλλαγή κουλτούρας.
18. (Ε.) Έλλειψη δεξιοτήτων και αντίσταση στις αλλαγές;
(Α.) Ναι.
19. (Ε.) Πολιτισμικά/δεξιοτεχνικά εμπόδια;
(Α.) Κυρίως δεξιότητες.
20. (Ε.) Εμπόδια εικόνας;
(Α.) Όχι.
21. (Ε.) Κίνδυνος φήμης ή αξιοπιστίας;
(Α.) Όχι ουσιαστικά.
22. (Ε.) Δημόσια κριτική;
(Α.) Όχι.
23. (Ε.) Άλλα εμπόδια εικόνας;
(Α.) Όχι.
24. (Ε.) Εσωτερικά ή εξωτερικά εμπόδια;
(Α.) Φόρτος εργασίας και έλλειψη χρηματοδότησης.
25. (Ε.) Επίδραση πολιτικών;
(Α.) Ναι.

26. (Ε.) Μέτρα πολιτικής;

(Α.) Στοχευμένη χρηματοδότηση, εκπαίδευση, ανάπτυξη λογισμικού.

27. (Ε.) Επιπλέον παράγοντες;

(Α.) Όχι.

28. (Ε.) Παράγοντες επιτυχούς εφαρμογής;

(Α.) Κατάλληλη υποδομή (hardware).

Interviewee No.6

1. (Ε.) Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;

(Α.) Στο Εθνικό Κέντρο Έρευνας Φυσικών Επιστημών «Δημόκριτος».

2. (Ε.) Ποια είναι τα κύρια καθήκοντα του οργανισμού σας;

(Α.) Ερευνητικός οργανισμός με αντικείμενο την επιστημονική έρευνα και την ανάπτυξη τεχνολογιών, συμπεριλαμβανομένης της Τεχνητής Νοημοσύνης.

3. (Ε.) Ποιος είναι ο ρόλος σας στον οργανισμό;

(Α.) Πρόεδρος του Διοικητικού Συμβουλίου.

4. (Ε.) Έχει υιοθετήσει ο οργανισμός σας συστήματα Τεχνητής Νοημοσύνης;

(Α.) Ναι.

5. (Ε.) Ποιοι ήταν οι κύριοι παράγοντες που οδήγησαν στην υιοθέτηση της Τεχνητής Νοημοσύνης;

(Α.) Η φύση του οργανισμού ως ερευνητικού φορέα με εξειδίκευση στην ΤΝ.

6. (Ε.) Είναι ο οργανισμός σας εξοικειωμένος με την έννοια της Πράσινης Τεχνητής Νοημοσύνης;

(Α.) Οι ερευνητές είναι εξοικειωμένοι, αλλά όχι σε οργανωσιακό επίπεδο.

7. (Ε.) Έχει υιοθετήσει ή σχεδιάζει να υιοθετήσει ο οργανισμός σας λύσεις Πράσινης ΤΝ;

(Α.) Έχουν υιοθετηθεί λύσεις όπως έξυπνοι μετρητές και αισθητήρες, σε αρχικό στάδιο.

8. (Ε.) Τι παρακινεί ή αποθαρρύνει τον οργανισμό από την υιοθέτηση Πράσινης ΤΝ;

(Α.) Ερευνητικά και διαχειριστικά κίνητρα για βελτίωση ενεργειακής διαχείρισης.

9. (Ε.) Εμπόδια Χρήσης Πράσινης ΤΝ:

9.1 Έλλειψη ποιοτικών δεδομένων – Σημαντικό εμπόδιο.

9.2 Πολυπλοκότητα προετοιμασίας δεδομένων – Πολύ σημαντική.

9.3 Πολυπλοκότητα σχεδιασμού συστημάτων – Πρόκληση.

9.4 Πολυπλοκότητα ανάπτυξης υποδομής – Ναι.

9.5 Έλλειψη τυποποιημένων διαδικασιών – Σοβαρό εμπόδιο.

9.6 Περιορισμένη διαθεσιμότητα εργαλείων – Όχι.

9.7 Περιορισμένη αυτοματοποίηση – Ναι.

9.8 Υψηλές απαιτήσεις συντήρησης – Πολύ υψηλές.

9.9 Άλλα εμπόδια – Οργανωσιακή κουλτούρα.

10. (Ε.) Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;

(Α.) Όχι ακόμη έτοιμος.

11. (Ε.) Περιορισμένα κοινωνικά ωφέλη;

(Α.) Όχι.

12. (Ε.) Κοινωνικά οφέλη έναντι κόστους;

(Α.) Μακροπρόθεσμα υπερτερούν.

13. (Ε.) Περιορισμοί ποιότητας δεδομένων;
(Α.) Ναι.
14. (Ε.) Υπάρχουν κίνδυνοι;
(Α.) Ναι.
15. (Ε.) Κίνδυνοι (δυσλειτουργία, μετρήσεις, εμπιστοσύνη, κανονισμοί);
(Α.) Όλα αποτελούν εμπόδια.
16. (Ε.) Άλλοι κανονιστικοί ή οικονομικοί κίνδυνοι;
(Α.) Δεν αναφέρθηκαν.
17. (Ε.) Παραδοσιακά εμπόδια;
(Α.) Οργανωσιακή κουλτούρα.
18. (Ε.) Επάρκεια υπαρχόντων συστημάτων;
(Α.) Όχι.
19. (Ε.) Αντίσταση στην αλλαγή / έλλειψη δεξιοτήτων;
(Α.) Ναι.
20. (Ε.) Εμπόδια εικόνας;
(Α.) Όχι.
21. (Ε.) Κίνδυνος αξιοπιστίας;
(Α.) Όχι.
22. (Ε.) Άλλα εμπόδια εικόνας;
(Α.) Όχι.
23. (Ε.) Εσωτερικά ή εξωτερικά εμπόδια;
(Α.) Υποδομές και κουλτούρα.
24. (Ε.) Πολιτικές που επηρεάζουν;
(Α.) Δεν επηρεάζεται ουσιαστικά.
25. (Ε.) Μέτρα πολιτικής;
(Α.) Δεν προσδιορίστηκαν.
26. (Ε.) Επιπλέον παράγοντες;
(Α.) Όχι.
27. (Ε.) —
(Α.) —
28. (Ε.) Παράγοντες επιτυχούς εφαρμογής;
(Α.) Κατάλληλος εξοπλισμός και ενιαία πλατφόρμα δεδομένων.

Interviewee No.7

1. (Ε.) Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;
(Α.) Εργάζομαι στο Εθνικό Κέντρο Έρευνας Φυσικών Επιστημών «Δημόκριτος», στο Ινστιτούτο Πληροφορικής και Τηλεπικοινωνιών, στον τομέα AI, HPC και Sustainability, ως ερευνητής Γ'.
2. (Ε.) Ποια είναι τα κύρια καθήκοντά σας;
(Α.) Το αντικείμενό μου αφορά τη χρήση υπολογιστικών εργαλείων για μοντελοποίηση φυσικών συστημάτων, την αξιοποίηση υπολογιστικών υποδομών υψηλών επιδόσεων και τη συμπληρωματική χρήση Τεχνητής Νοημοσύνης σε περιβαλλοντικές και κλιματικές εφαρμογές.
3. (Ε.) Πώς συνδέεται ο ρόλος σας με τον οργανισμό και το Ινστιτούτο;
(Α.) Η επιστημονική μου πορεία ξεκίνησε στον Δημόκριτο το 2009. Από το 2017—

2018 η Τεχνητή Νοημοσύνη ενσωματώθηκε ως συμπληρωματικό εργαλείο, λόγω εμπλοκής μου σε hardware, software και δημιουργία υπολογιστικής υποδομής.

4. (Ε.) Έχει υιοθετήσει ο οργανισμός σας συστήματα Τεχνητής Νοημοσύνης;

(Α.) Σε οργανωσιακό επίπεδο όχι. Σε ατομικό επίπεδο, πολλοί ερευνητές χρησιμοποιούν εργαλεία ΤΝ χωρίς ενιαία στρατηγική.

5. (Ε.) Με ποιον τρόπο χρησιμοποιούνται αυτά τα εργαλεία;

(Α.) Μέσω ακαδημαϊκής άδειας Microsoft, με χρήση να εξαρτάται από την πρωτοβουλία κάθε ερευνητή.

6. (Ε.) Είναι ο οργανισμός σας εξοικειωμένος με την έννοια της Πράσινης Τεχνητής Νοημοσύνης;

(Α.) Σε επίπεδο ερευνητών ναι, αλλά όχι σε οργανωσιακό επίπεδο.

7. (Ε.) Υπάρχει στρατηγική ή ετοιμότητα του οργανισμού για Πράσινη ΤΝ;

(Α.) Όχι σε θεσμικό επίπεδο, μόνο αποσπασματικές πρακτικές.

8. (Ε.) Τι εμποδίζει τον οργανισμό από την υιοθέτηση συστημάτων ΤΝ σε οργανωσιακό επίπεδο;

(Α.) Η πολυθεματικότητα του οργανισμού, η ηλικιακή σύνθεση του προσωπικού και οι αργοί ρυθμοί λήψης αποφάσεων.

9. (Ε.) Ποια γενικά εμπόδια σχετίζονται με την υιοθέτηση Πράσινης ΤΝ;

(Α.) Η ταχεία εξέλιξη της ΤΝ, η έλλειψη χρόνου, η πολυπλοκότητα υποδομών και η απουσία κεντρικής στρατηγικής.

10. (Ε.) Εμπόδια Χρήσης Πράσινης ΤΝ:

10.1 Έλλειψη υψηλής ποιότητας δεδομένων – Ναι.

10.2 Πολυπλοκότητα προετοιμασίας δεδομένων – Ναι.

10.3 Πολυπλοκότητα σχεδιασμού ενεργειακά αποδοτικών συστημάτων – Ναι.

10.4 Πολυπλοκότητα ανάπτυξης υποδομών – Ναι.

10.5 Περιορισμένη διαθεσιμότητα εργαλείων – Ναι.

10.6 Περιορισμένη αυτοματοποίηση – Ναι.

10.7 Υψηλές απαιτήσεις συντήρησης – Όχι ιδιαίτερα.

10.8 Άλλα εμπόδια – Ηλικία, εκπαίδευση και ανάγκη upskilling.

11. (Ε.) Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;

(Α.) Δεν είναι έτοιμος.

12. (Ε.) Η Πράσινη ΤΝ προσφέρει περιορισμένα κοινωνικά οφέλη;

(Α.) Όχι.

13. (Ε.) Τα οφέλη είναι χαμηλότερα από το κόστος;

(Α.) Όχι για δημόσιο οργανισμό.

14. (Ε.) Υπάρχουν κίνδυνοι υιοθέτησης;

(Α.) Ναι.

15. (Ε.) Ανακριβείς μετρήσεις βιωσιμότητας;

(Α.) Ναι.

16. (Ε.) Θέματα εμπιστοσύνης στα αποτελέσματα;

(Α.) Όχι ιδιαίτερα.

17. (Ε.) Άλλοι κίνδυνοι;

(Α.) Η κατανόηση χρήσης στην καθημερινή λειτουργία.

18. (Ε.) Τα υπάρχοντα συστήματα είναι επαρκή;

(Α.) Όχι.

19. (Ε.) Υπάρχει αντίσταση στην αλλαγή και έλλειψη δεξιοτήτων;

(Α.) Ναι.

20. (Ε.) Υπάρχουν άλλα παραδοσιακά εμπόδια;
(Α.) Όχι.
21. (Ε.) Υπάρχουν ανησυχίες για τη φήμη;
(Α.) Ναι, σε διοικητικό επίπεδο.
22. (Ε.) Κίνδυνος βλάβης αξιοπιστίας;
(Α.) Ναι.
23. (Ε.) Άλλα εμπόδια εικόνας;
(Α.) Όχι.
24. (Ε.) Εσωτερικά ή εξωτερικά εμπόδια;
(Α.) Εσωτερικά: κουλτούρα και learning curve. Εξωτερικά: κόστος και χρηματοδότηση.
25. (Ε.) Επηρεάζουν οι εθνικές ή ευρωπαϊκές πολιτικές;
(Α.) Ναι.
26. (Ε.) Ποια μέτρα πολιτικής θα βοηθούσαν;
(Α.) Πρόσβαση σε χρηματοδοτικά εργαλεία μέσω ESG/SDG scoring.
27. (Ε.) Υπάρχουν επιπλέον εμπόδια;
(Α.) Όχι.
28. (Ε.) Ποιοι είναι οι βασικοί παράγοντες επιτυχούς εφαρμογής;
(Α.) Αλλαγή νοοτροπίας, εκπαίδευση και εξασφαλισμένη χρηματοδότηση.

Interviewee No.8

Q1. Σε ποιον φορέα εργάζεστε;

Εργάζομαι στην ΕΔΥΤΕ (GRNET), έναν οργανισμό του ελληνικού δημοσίου που λειτουργεί με τη μορφή ανώνυμης εταιρείας.

Q2. Ποια είναι η αποστολή του οργανισμού;

Ο οργανισμός μου δραστηριοποιείται σε πέντε βασικούς πυλώνες: δίκτυα νέας γενιάς, υπολογιστική ισχύ, πληροφοριακά συστήματα για το Δημόσιο, εκπαίδευση πολιτών και τεχνητή νοημοσύνη.

Q3. Ποιος είναι ο ρόλος σας;

Μέχρι πρόσφατα ήμουν διευθυντής ηλεκτρονικής διακυβέρνησης και πλέον λειτουργώ ως σύμβουλος σε θέματα ψηφιακού μετασχηματισμού.

Q4. Έχει υιοθετήσει ο οργανισμός σας συστήματα TN;

Ναι, έχουμε υιοθετήσει συστήματα τεχνητής νοημοσύνης σχετικά νωρίς, κυρίως για να προσφέρουμε υπηρεσίες σε φορείς του Δημοσίου.

Q5. Ποιοι παράγοντες οδήγησαν στην υιοθέτηση TN;

Η υιοθέτηση προήλθε κυρίως από ευρωπαϊκές κατευθύνσεις που ενσωματώθηκαν σε εθνικές πολιτικές και υλοποιήθηκαν μέσω ευρωπαϊκών και εθνικών έργων.

Q6. Είστε εξοικειωμένος με την Πράσινη TN;

Δεν ήμουν εξοικειωμένος με την Πράσινη TN όπως ορίζεται στη βιβλιογραφία· μέχρι πρόσφατα εστιάζαμε κυρίως στο ενεργειακό αποτύπωμα των data centers.

Q7. Υπάρχει πρόθεση υιοθέτησης Πράσινης TN;

Το τελευταίο διάστημα εξετάζουμε τη χρήση μικρότερων, τοπικών γλωσσικών μοντέλων με χαμηλότερο ενεργειακό και οικονομικό κόστος.

Q8. Ποια είναι τα βασικά κίνητρα για Πράσινη ΤΝ;

Το βασικό κίνητρο είναι το χαμηλότερο κόστος σε σχέση με τα εμπορικά μοντέλα, καθώς και η ανάγκη για ψηφιακή κυριαρχία και έλεγχο των δεδομένων.

Q9. Ποια εμπόδια δυσχεραίνουν τη χρήση Πράσινης ΤΝ;

Τα κυριότερα εμπόδια είναι η έλλειψη ποιοτικών δεδομένων, η τεχνολογική πολυπλοκότητα και η αυξημένη ανάγκη συντήρησης των συστημάτων.

Q10. Υπάρχουν εμπόδια χρήστη;

Ναι, κυρίως λόγω της συνήθειας χρήσης έτοιμων εμπορικών λύσεων και της έλλειψης τεχνογνωσίας.

Q11. Πόσο έτοιμος είναι ο οργανισμός τεχνολογικά;

Βρισκόμαστε ακόμη σε αρχικό στάδιο και δεν θα έλεγα ότι είμαστε πλήρως έτοιμοι, ιδίως σε επίπεδο κλίμακας.

Q12. Υπάρχουν εμπόδια αξίας;

Τα οφέλη της Πράσινης ΤΝ δεν είναι άμεσα αντιληπτά, ιδιαίτερα όταν οι υπάρχουσες λύσεις θεωρούνται δωρεάν.

Q13. Υπάρχουν εμπόδια κινδύνου;

Υπάρχει ανησυχία σχετικά με την αξιοπιστία και την αποτελεσματικότητα μη επώνυμων λύσεων.

Q14. Πώς επηρεάζει η εμπιστοσύνη την υιοθέτηση;

Η έλλειψη εμπιστοσύνης λειτουργεί αποτρεπτικά, ειδικά όταν συγκρίνεται με γνωστούς παρόχους.

Q15. Υπάρχουν ζητήματα κανονιστικής συμμόρφωσης;

Δεν θεωρώ ότι υπάρχουν ιδιαίτερες διαφορές σε σχέση με τα υπάρχοντα κανονιστικά πλαίσια.

Q16. Πώς επηρεάζει η ιδιωτικότητα δεδομένων;

Τα τοπικά μοντέλα θεωρώ ότι μειώνουν τον κίνδυνο, καθώς τα δεδομένα παραμένουν εσωτερικά.

Q17. Υπάρχουν σφάλματα ή τεχνικοί κίνδυνοι;

Σφάλματα μπορεί να υπάρξουν, αλλά η έκτασή τους είναι συνήθως περιορισμένη σε τοπικές λύσεις.

Q18. Υπάρχουν πολιτισμικά ή οργανωσιακά εμπόδια;

Υπάρχει έντονη προτίμηση σε επώνυμα προϊόντα και αντίσταση σε εναλλακτικές λύσεις.

Q19. Υπάρχουν ζητήματα δεξιοτήτων;

Υπάρχει ανάγκη για εκπαίδευση προσωπικού σε νέα εργαλεία και υποδομές.

Q20. Πώς επηρεάζει το εξωτερικό περιβάλλον;

Οι πιέσεις από μεγάλους παρόχους τεχνολογίας επηρεάζουν τις αποφάσεις υιοθέτησης.

Q21. Πώς επηρεάζει η εικόνα και η φήμη;

Υπάρχει φόβος ότι μη επώνυμες λύσεις μπορεί να πλήξουν τη φήμη του οργανισμού.

Q22. Ποιος είναι ο ρόλος της διοίκησης;

Η διοίκηση διαδραματίζει κρίσιμο ρόλο στη λήψη αποφάσεων και στην αποδοχή της καινοτομίας.

Q23. Πώς επηρεάζουν οι πολιτικές αποφάσεις;

Οι ευρωπαϊκές και εθνικές πολιτικές είναι καθοριστικές για την υιοθέτηση της Πράσινης ΤΝ.

Q24. Ποια εσωτερικά και εξωτερικά εμπόδια υπάρχουν;

Εσωτερικά εμπόδια είναι η τεχνογνωσία, ενώ εξωτερικά η επιρροή των μεγάλων προμηθευτών.

Q25. Ποια πολιτικά μέτρα θα βοηθούσαν;

Χρειάζονται κίνητρα και ευνοϊκές ρυθμίσεις υπέρ ενεργειακά αποδοτικών λύσεων.

Q26. Ποια είναι τα βασικά οφέλη της Πράσινης ΤΝ;

Μείωση κόστους, μείωση ενεργειακού αποτυπώματος και καλύτερος έλεγχος δεδομένων.

Q27. Κάτι επιπλέον που θα θέλατε να προσθέσετε;

Είναι σημαντικό να πειστούν οι decision-makers ότι υπάρχουν ισοδύναμες, βιώσιμες εναλλακτικές λύσεις.

Interviewee No.9

E1. Οργανισμός

E: Σε ποιον οργανισμό εργάζεστε; Ποιος είναι ο χαρακτήρας του;

A: A. Ο οργανισμός ονομάζεται SciFY (Science For You), μη κερδοσκοπικός οργανισμός με τεχνολογικό χαρακτήρα. Ένας από τους βασικούς πυλώνες είναι η Τεχνητή Νοημοσύνη και πρόσφατα προστέθηκε πυλώνας για το περιβάλλον και το Green AI.

E2–E3. Ρόλος & Καθήκοντα

E: Ποια είναι τα κύρια καθήκοντα του οργανισμού και ποιος ο ρόλος σας;

A: A. Στόχος είναι η αξιοποίηση ερευνητικών αποτελεσμάτων προς όφελος της κοινωνίας. Ο ρόλος μου είναι AI engineer και AI expert, με ανάπτυξη λύσεων ΤΝ και εκπαίδευση οργανισμών.

E4. Υιοθέτηση ΤΝ

E: Έχει υιοθετήσει ο οργανισμός συστήματα ΤΝ; Είναι πράσινα;

A: A. Ναι, χρησιμοποιούνται λύσεις ΤΝ. Η πράσινη διάσταση αφορά τόσο ενεργειακά αποδοτικούς αλγορίθμους όσο και εφαρμογές AI4Green.

E5. Παράγοντες υιοθέτησης

E: Ποιοι παράγοντες οδήγησαν στην υιοθέτηση ΤΝ;

A: A. Η ΤΝ είναι στον πυρήνα της αποστολής του οργανισμού από την ίδρυσή του.

E6. Εξοικείωση με Green AI

E: Ο οργανισμός είναι εξοικειωμένος με την έννοια Green AI;

A: A. Η εξοικείωση αναπτύχθηκε κυρίως τα τελευταία τρία χρόνια.

E7. Στρατηγική Green AI

E: Υπάρχει στρατηγική ή σχέδιο υιοθέτησης;

A: A. Οι περισσότερες λύσεις είναι πράσινες κυρίως λόγω κόστους και βιωσιμότητας.

E8. Κίνητρα / Αποθάρρυνση

E: Τι παρακινεί ή αποθαρρύνει την υιοθέτηση;

A: Α. Κίνητρα είναι το κόστος και το περιβαλλοντικό αποτύπωμα. Αποθάρρυνση προκαλεί η μόδα των ενεργοβόρων LLMs.

E9–E11. Εμπόδια χρήσης

E: Τεχνικά και οργανωτικά εμπόδια (δεδομένα, υποδομές, εργαλεία);

A: Α. Έλλειψη ποιοτικών δεδομένων, πολυπλοκότητα προετοιμασίας, απουσία αυτοματοποίησης ενεργειακής βελτιστοποίησης.

E12. Ετοιμότητα

E: Πόσο έτοιμος είναι ο οργανισμός;

A: Α. Θεωρείται τεχνολογικά έτοιμος.

E13–E14. Εμπόδια αξίας

E: Τα οφέλη υπερβαίνουν το κόστος;

A: Α. Τα κοινωνικά οφέλη είναι υψηλά, αλλά σε οργανωσιακό επίπεδο το κόστος αποτελεί πρόκληση.

E15–E17. Κίνδυνοι

E: Υπάρχουν κίνδυνοι και αβεβαιότητες;

A: Α. Κίνδυνοι σχετίζονται με δεδομένα, ηθική, φήμη και κανονιστική ευθύνη.

E18–E20. Παραδοσιακά εμπόδια

E: Υπάρχουν πολιτισμικά ή οργανωσιακά εμπόδια;

A: Α. Το βασικό εμπόδιο είναι η αλλαγή κουλτούρας και η εκπαίδευση όλων των stakeholders.

E21–E23. Εικόνα & Φήμη

E: Υπάρχουν κίνδυνοι για την εικόνα του οργανισμού;

A: Α. Υπάρχουν θεωρητικά, αλλά δεν λειτουργούν αποτρεπτικά.

E24. Εσωτερικά/Εξωτερικά εμπόδια

E: Ποια εμπόδια παρεμποδίζουν την υιοθέτηση;

A: Α. Το κόστος συντήρησης και η αστάθεια εξωτερικών παραγόντων (licenses, servers).

E25–E28. Πολιτικές & Μέλλον

E: Τι θα ενίσχυε την υιοθέτηση στο μέλλον;

A: Α. Χρηματοδοτικά κίνητρα, πολιτικές βιωσιμότητας και ενσωμάτωση σε ESG/SDGs.

Interviewee No.10

1. (E.) Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;

(A.) Εργάζομαι στην ΕΛΑΚ, έναν μη κερδοσκοπικό οργανισμό ανοιχτών τεχνολογιών που έχει ιδρυθεί από πανεπιστήμια και εθνικά κέντρα, με σκοπό την προώθηση του ανοιχτού λογισμικού, των ανοιχτών δεδομένων, της ανοιχτής διακυβέρνησης και των ανοιχτών προτύπων στο δημόσιο, στις επιχειρήσεις και στην εκπαίδευση.

2. (E.) Ποια είναι τα κύρια καθήκοντα του οργανισμού και ο ρόλος σας;

(A.) Ο οργανισμός δραστηριοποιείται στην προώθηση ανοιχτών τεχνολογιών. Ο ρόλος μου αφορά τη στρατηγική, την τεχνολογική ανάπτυξη και την υποστήριξη έργων που σχετίζονται με TN και ανοιχτές υποδομές.

3. (Ε.) Πόσο έτοιμος είναι ο οργανισμός σας και ποια η στρατηγική του για την Πράσινη ΤΝ;
(Α.) Η πράσινη ΤΝ είναι συμβατή με τις αρχές του οργανισμού, καθώς τα ανοιχτά και τοπικά μοντέλα έχουν μικρότερο ενεργειακό αποτύπωμα από τις λύσεις hyperscalers.
4. (Ε.) Έχει υιοθετήσει ο οργανισμός σας συστήματα ΤΝ;
(Α.) Ναι, έχει υιοθετήσει και συμβάλλει ενεργά στην ανάπτυξη συστημάτων ΤΝ.
5. (Ε.) Ποιοι παράγοντες οδήγησαν στην υιοθέτηση ΤΝ;
(Α.) Η ΤΝ είναι εγγενές αποτέλεσμα των ανοιχτών τεχνολογιών και της φιλοσοφίας του οργανισμού.
6. (Ε.) Είναι ο οργανισμός εξοικειωμένος με την Πράσινη ΤΝ;
(Α.) Ναι, αρκετά, καθώς τα ανοιχτά και μικρής κλίμακας μοντέλα είναι εγγενώς πιο φιλικά προς το περιβάλλον.
7. (Ε.) Έχει υιοθετήσει ή σχεδιάζει να υιοθετήσει λύσεις Πράσινης ΤΝ;
(Α.) Ναι, στο πλαίσιο ευρωπαϊκού έργου, με ανάπτυξη τοπικά φιλοξενούμενων μοντέλων μικρής κλίμακας.
8. (Ε.) Τι παρακινεί ή αποθαρρύνει την υιοθέτηση Πράσινης ΤΝ;
(Α.) Δεν υπάρχει αποθάρρυνση· η Πράσινη ΤΝ παρακινείται λόγω συμβατότητας με τις αξίες και τη βιωσιμότητα.
9. (Ε.) Ποια γενικά εμπόδια σχετίζονται με την υιοθέτηση Πράσινης ΤΝ;
(Α.) Τα εμπόδια αφορούν κυρίως την ωρίμανση της αγοράς, τη γνώση και τη στρατηγική διαφοροποίηση οργανισμών.
10. (Ε.) Εμπόδια χρήσης (δεδομένα, υποδομές, εργαλεία, αυτοματοποίηση, συντήρηση);
(Α.) Υπάρχουν εμπόδια όπως η έλλειψη ποιοτικών δεδομένων, η πολυπλοκότητα προετοιμασίας, ο σχεδιασμός ενεργειακά αποδοτικών υποδομών, η έλλειψη εργαλείων και αυτοματοποίησης. Η συντήρηση δεν θεωρείται εμπόδιο αν οι αρχές είναι ενσωματωμένες εκ του σχεδιασμού.
11. (Ε.) Υπάρχουν άλλα εμπόδια χρήσης;
(Α.) Όχι, δεν εντοπίζονται επιπλέον εμπόδια.
12. (Ε.) Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;
(Α.) Ο οργανισμός βρίσκεται σε φάση διερεύνησης και πειραματισμού.
13. (Ε.) Η Πράσινη ΤΝ προσφέρει περιορισμένα κοινωνικά οφέλη;
(Α.) Όχι, τα κοινωνικά οφέλη θεωρούνται υψηλά.

14. (Ε.) Η Πράσινη ΤΝ προσφέρει περιορισμένη επιχειρηματική αξία;
(Α.) Εξαρτάται από τον τύπο και το μέγεθος του οργανισμού.
15. (Ε.) Τα κοινωνικά οφέλη είναι χαμηλότερα από το κόστος;
(Α.) Όχι, αξίζει να επιδιωχθεί η επένδυση.
16. (Ε.) Τα οφέλη για τον οργανισμό είναι χαμηλότερα από το κόστος;
(Α.) Για μικρούς οργανισμούς, η Πράσινη ΤΝ αποτελεί τη μόνη βιώσιμη επιλογή.
17. (Ε.) Το υψηλό κόστος επένδυσης αποτελεί εμπόδιο;
(Α.) Ναι, ιδιαίτερα βραχυπρόθεσμα.
18. (Ε.) Υπάρχουν παραδοσιακά ή πολιτισμικά εμπόδια;
(Α.) Όχι ιδιαίτερα, ο οργανισμός είναι ευέλικτος και ανοιχτός στην αλλαγή.
19. (Ε.) Υπάρχει αντίσταση στην αλλαγή ή έλλειψη δεξιοτήτων;
(Α.) Η εκπαίδευση αντιμετωπίζεται άμεσα και ενσωματώνεται στις πρακτικές.
20. (Ε.) Υπάρχουν άλλα παραδοσιακά εμπόδια;
(Α.) Όχι.
21. (Ε.) Υπάρχουν εμπόδια εικόνας ή φήμης;
(Α.) Όχι, ο οργανισμός είναι έτοιμος να υποστηρίξει τις επιλογές του.
22. (Ε.) Κίνδυνος βλάβης αξιοπιστίας ή κακής απόδοσης;
(Α.) Ναι, αποτελεί υπαρκτό κίνδυνο.
23. (Ε.) Υπάρχουν επιπλέον εμπόδια εικόνας;
(Α.) Όχι.
24. (Ε.) Υπάρχουν εσωτερικά ή εξωτερικά εμπόδια;
(Α.) Όχι ουσιαστικά, ο οργανισμός βρίσκεται σε στάδιο διερεύνησης.
25. (Ε.) Επηρεάζουν οι εθνικές ή ευρωπαϊκές πολιτικές;
(Α.) Ναι, επηρεάζουν σημαντικά.
26. (Ε.) Ποια μέτρα πολιτικής θα βοηθούσαν;
(Α.) Επιδοτήσεις, φορολογικά κίνητρα και καμπάνιες ενημέρωσης.
27. (Ε.) Υπάρχουν επιπλέον εμπόδια;
(Α.) Όχι.
28. (Ε.) Ποιοι είναι οι βασικοί παράγοντες επιτυχίας;
(Α.) Η αποδοτικότητα και η ευθυγράμμιση με τον σκοπό του οργανισμού.

1. (Ε.) Σε ποιον κυβερνητικό ή ιδιωτικό οργανισμό εργάζεστε;
(Α.) Εργάζομαι στο ΕΚΕΦΕ «Δημόκριτος», ένα από τα μεγαλύτερα ερευνητικά κέντρα της Ελλάδας, με έδρα την Αθήνα.
2. (Ε.) Ποια είναι τα κύρια καθήκοντα του οργανισμού και ο ρόλος σας;
(Α.) Εργάζομαι ως ερευνητής σε ερευνητικά προγράμματα και είμαι επικεφαλής του Κέντρου Δικτύων του οργανισμού.
3. (Ε.) Ποια είναι η στρατηγική ετοιμότητα και οι πόροι του οργανισμού για Πράσινη ΤΝ;
(Α.) Η ετοιμότητα βρίσκεται σε πρώιμο στάδιο και εξαρτάται από την ανάπτυξη κατάλληλων υποδομών και πόρων.
4. (Ε.) Έχει υιοθετήσει ο οργανισμός συστήματα ΤΝ;
(Α.) Δεν υπάρχει οργανωμένη, κεντρική υιοθέτηση ΤΝ. Ωστόσο, γίνεται εκτεταμένη χρήση εργαλείων ΤΝ σε ατομικό επίπεδο από ερευνητές και εργαζόμενους.
5. (Ε.) Ποιοι παράγοντες οδήγησαν στην υιοθέτηση ΤΝ;
(Α.) Η αύξηση παραγωγικότητας, η υποστήριξη ερευνητικής δραστηριότητας και η βελτίωση εργασιακών διαδικασιών.
6. (Ε.) Είναι ο οργανισμός εξοικειωμένος με την Πράσινη ΤΝ;
(Α.) Η έννοια είναι γνωστή μόνο σε μικρό μέρος ερευνητών και δεν αποτελεί ακόμη οργανωμένη στρατηγική.
7. (Ε.) Έχει υιοθετήσει ή σχεδιάζει να υιοθετήσει Πράσινη ΤΝ;
(Α.) Υπάρχει πρόθεση μελλοντικής υιοθέτησης, κυρίως μέσω ιδιόκτητων υποδομών και έργων.
8. (Ε.) Τι παρακινεί ή αποθαρρύνει την υιοθέτηση Πράσινης ΤΝ;
(Α.) Δεν υπάρχει αποθάρρυνση, αλλά απουσιάζει οργανωμένη στρατηγική.
9. (Ε.) Υπάρχουν γενικά εμπόδια υιοθέτησης Πράσινης ΤΝ;
(Α.) Τα βασικά εμπόδια σχετίζονται με την ωρίμανση της αγοράς και την έλλειψη δεδομένων.
10. (Ε.) Εμπόδια χρήσης Πράσινης ΤΝ (υποερωτήματα):
(Α.) 10.1 Έλλειψη ποιοτικών δεδομένων – Ναι, τα δεδομένα είναι πρώιμα.
10.2 Πολυπλοκότητα προετοιμασίας δεδομένων – Ναι.
10.3 Πολυπλοκότητα σχεδιασμού ενεργειακά αποδοτικών συστημάτων – Ναι.
10.4 Πολυπλοκότητα ανάπτυξης υποδομών – Ναι.
10.5 Έλλειψη τυποποιημένων διαδικασιών – Όχι ακόμη κρίσιμο.
10.6 Περιορισμένη διαθεσιμότητα εργαλείων και υψηλό κόστος – Ναι.
10.7 Περιορισμένη αυτοματοποίηση – Ναι.
10.8 Υψηλές απαιτήσεις συντήρησης – Μέτριο εμπόδιο.

11. (Ε.) Υπάρχουν άλλα εμπόδια χρήσης;
(Α.) Ναι, έλλειψη εξειδικευμένου τεχνικού προσωπικού (operational).
12. (Ε.) Πόσο έτοιμος είναι τεχνολογικά ο οργανισμός;
(Α.) Σε πολύ χαμηλό επίπεδο (περίπου 1,5/5).
13. (Ε.) Προσφέρει η Πράσινη ΤΝ περιορισμένα κοινωνικά οφέλη;
(Α.) Όχι, τα κοινωνικά οφέλη θεωρούνται σημαντικά.
14. (Ε.) Προσφέρει περιορισμένη επιχειρηματική αξία;
(Α.) Όχι, η επιχειρηματική αξία δεν θεωρείται περιορισμένη.
15. (Ε.) Τα κοινωνικά οφέλη είναι χαμηλότερα από το κόστος;
(Α.) Όχι.
16. (Ε.) Τα οφέλη για τον οργανισμό είναι χαμηλότερα από το κόστος;
(Α.) Ενδέχεται να αποτελέσει εμπόδιο σε επίπεδο διοίκησης.
17. (Ε.) Το υψηλό κόστος επένδυσης αποτελεί εμπόδιο;
(Α.) Ναι, είναι σημαντικό εμπόδιο.
18. (Ε.) Υπάρχουν παραδοσιακά ή πολιτισμικά εμπόδια;
(Α.) Ναι, προτεραιοποίηση άλλων προβλημάτων και άνιση εξοικείωση προσωπικού με την ΤΝ.
19. (Ε.) Υπάρχει αντίσταση στην αλλαγή ή έλλειψη δεξιοτήτων;
(Α.) Ναι, ιδιαίτερα έλλειψη δεξιοτήτων και οργανωμένης εκπαίδευσης.
20. (Ε.) Υπάρχουν άλλα παραδοσιακά εμπόδια;
(Α.) Ναι, ανεπαρκής διατομεακή συνεργασία.
21. (Ε.) Υπάρχουν εμπόδια εικόνας ή φήμης;
(Α.) Μέτρια, κυρίως λόγω πιθανής δημόσιας κριτικής.
22. (Ε.) Κίνδυνος βλάβης αξιοπιστίας ή δεδομένων;
(Α.) Υψηλός, κυρίως σε θέματα προστασίας δεδομένων και κανονισμών.
23. (Ε.) Υπάρχουν επιπλέον εμπόδια εικόνας;
(Α.) Ναι, ηθικά διλήμματα σε dual-use εφαρμογές.
24. (Ε.) Ποια εσωτερικά ή εξωτερικά εμπόδια υπάρχουν;
(Α.) Κανονιστική ασάφεια, έλλειψη κοινών προτύπων βιωσιμότητας, εξάρτηση από χρηματοδότηση.
25. (Ε.) Επηρεάζουν οι εθνικές ή ευρωπαϊκές πολιτικές;
(Α.) Ναι, σε πολύ μεγάλο βαθμό μέσω χρηματοδοτήσεων.

26. (Ε.) Ποια μέτρα πολιτικής θα βοηθούσαν;

(Α.) Ένταξη βιωσιμότητας ως κριτηρίου χρηματοδότησης και στρατηγικής.

27. (Ε.) Υπάρχουν επιπλέον εμπόδια ή παράγοντες;

(Α.) Η απουσία σαφούς εθνικής στρατηγικής.

28. (Ε.) Ποιοι είναι οι βασικοί παράγοντες επιτυχίας;

(Α.) Σαφές κανονιστικό πλαίσιο, ευρωπαϊκή στρατηγική και εκπαίδευση ανθρώπινου δυναμικού.