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GREEN AI AND AI ACT: PIONEERING LEGISLATION OR MERELY AN ENVIRONMENTAL STATEMENT?

IA VERDE Y LA LEY IA ¿LEGISLACIÓN PIONERA O SIMPLE DECLARACIÓN DE INTENCIONES EN MATERIA MEDIOAMBIENTAL?

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ABSTRACT: This article examines how the European Union's environmental perspective on artificial intelligence has evolved, contrasting the high expectations set forth by the European Green Deal with the subsequent AI Act. Although the European Green Deal acknowledged AI's potential to enhance energy efficiency, it did not thoroughly address water and energy consumption or the handling of e-waste arising from the development of large deep learning models. Subsequently, the AI White Paper delved more deeply into the environmental dimension of this technology. However, the AI Act—enacted in 2024—does not fully translate these proposals into concrete obligations. The

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article discusses the main provisions of the AI Act that refer to sustainability, underscoring the absence of direct mechanisms to limit energy consumption, mitigate water footprints, or ensure proper electronic waste management. In this context, two *de lege ferenda* measures are proposed to remedy these shortcomings: the mandatory inclusion of environmental impact factors in competitive AI benchmarks, and the implementation of an environmental labeling system that informs consumers about the sustainability of the data centers where models operate.

RESUM: Aquest article examina com ha evolucionat la perspectiva mediambiental de la Unió Europea sobre la intel·ligència artificial, tot contrastant les elevades expectatives fixades pel Pacte Verd Europeu amb l'Acte IA que el va seguir. Malgrat que el Pacte Verd reconeixia el potencial de la IA per millorar l'eficiència energètica, no va abordar de manera exhaustiva el consum d'aigua i d'energia ni la gestió dels residus electrònics derivats del desenvolupament de grans models d'aprenentatge profund. Posteriorment, el Llibre Blanc sobre IA va aprofundir més en la dimensió ambiental d'aquesta tecnologia; tanmateix, l'Acte IA —aprovat el 2024— no tradueix completament aquestes propostes en obligacions concretes. L'article analitza les principals disposicions de l'Acte IA relacionades amb la sostenibilitat, incidint en l'absència de mecanismes directes per limitar el consum energètic, mitigar la petjada hídrica o garantir una gestió adequada dels residus electrònics. En aquest context, es proposen dues mesures de lege ferenda per resoldre aquestes mancances: la inclusió obligatòria de factors d'impacte ambiental en els benchmarks competitius de IA, i la implementació d'un sistema d'etiquetatge mediambiental que informi els consumidors sobre la sostenibilitat dels centres de dades on operen els models.

RESUMEN: El presente artículo analiza la evolución de la perspectiva medioambiental en la Unión Europea en torno a la Inteligencia Artificial, contrastando las expectativas generadas por el European Green Deal y la reciente Ley IA. Aunque el Green Deal reconoció la relevancia de la IA para mejorar la eficiencia energética, su enfoque no contempló a fondo el consumo de recursos hídricos y energéticos, ni la gestión del *e-waste* vinculado al desarrollo de grandes modelos de aprendizaje profundo. Posteriormente, el Libro Blanco de la IA profundizó en la dimensión ambiental de esta tecnología, pero la Ley IA —aprobada en 2024— no acaba de materializar estas propuestas en obligaciones concretas. Se exponen los principales artículos de la Ley IA que se refieren a la sostenibilidad, señalando la ausencia de mecanismos directos para limitar el consumo energético, mitigar la huella hídrica o gestionar adecuadamente los residuos electrónicos. En este contexto, se formulan dos medidas de *lege ferenda* para corregir esas carencias: la introducción obligatoria de factores de impacto ambiental en los *benchmarks* competitivos de IA, y la implementación de un sistema de etiquetado ambiental que informe al consumidor sobre la sostenibilidad de los centros de datos donde operan los modelos.

KEY WORDS: Green AI – AI Act – Artificial intelligence – European Union – Sustainability – Data centers.

PARAULES CLAU: Green AI – Acte IA – Intel·ligència Artificial – Unió Europea – Sostenibilitat – Centres de dades.

PALABRAS CLAVE: Green AI – Ley IA – Inteligencia artificial – Unión Europea – Sostenibilidad – Centros de datos.

I. THE GREEN DEAL AS A PRECURSOR OF THE EU'S ENVIRONMENTAL AWARENESS CONCERNING ARTIFICIAL INTELLIGENCE

It is broadly acknowledged that, based on a clear reading of, among others, articles 191 and 193 of the Treaty on the Functioning of the European Union (hereinafter, the "TFEU"), this institution maintains a strong commitment to implementing public policies aimed at environmental protection, including the efficient management of water and energy resources (Campins Eritja, 2018). In this regard, it should be noted that the aforementioned articles explicitly refer to “the conservation, protection, and improvement of the quality of the environment in the European Union,” as well as to the protective measures established to that end.

Moreover, classical administrative law scholars such as Harlow and Rawlings (2009:195–201) pointed out that whenever a particular law grants an entity competence over certain matters, it inevitably nurtures the expectation that policies will be developed to address a current issue—or one foreseen to arise within a given timeframe. This same rationale was subsequently expanded upon in the context of European law (Majone, 2014) and its orientation toward environmental protection and the promotion of sustainability. In other words, if the TFEU grants the EU competence in environmental matters, it is because (a) it recognizes a potential or actual concern of social relevance, and/or (b) it expects the European Union to take a conspicuously proactive stance on the matter.

Accordingly, various scholars have formulated their own critical assessments of the milestones in the European Union’s environmental policy. Such scholarly commentary is certainly diverse: some authors present a favorable view (Haigh, 2015: 31), contending that European initiatives such as the Paris Climate Conference, the Kyoto Protocol, or the EU’s 2020 Climate and Energy Package constitute fundamental milestones. Others (Jordan & Lenschow, 2010) underscore that European commitments heavily hinge on the political will of national governments, arguing that the European Union tends not to adopt compulsory compliance measures in this domain. In that same context, as early as 2020, certain Members of the European Parliament—among them Eugen Jurzyca—criticized the European Commission on grounds that the EU’s 2020 Climate and Energy Package had neglected the matter of CO2 emissions tied to artificial intelligence (hereinafter “AI”) (European Parliament, 2020).

Regarding this latter point, a noteworthy critique in scholarly circles posits that the European Commission, authorized under articles 258 through 260 of the

TFEU, often acts in accordance with interests that can be more or less politically charged. This shift away from sanctioning noncompliant national governments toward a more informal supervisory role has been highlighted by some authors (Kelemen and Pavone, 2022: 292–299), who note that any enforcement mechanism limited by political considerations has also limited utility. In other words, the European Union does not generally enforce direct, interventionist environmental protection mechanisms; moreover, the penalty associated with governmental noncompliance is indeed subject – more or less and depending on the issue - to political nuance.

Hence, prior to the adoption of Regulation (EU) 2024/1689 of the European Parliament and of the Council, of June 13, 2024 (Hereinafter, the “AI Act”), the European Union was operating within a turbulent legislative environment, as will be discussed below, due to the approval of numerous EU environmental laws whose implementation across member states was variably effective. In this pre–AI Act context, scholars identified three key environmental challenges the EU was addressing—and would need to continue addressing—regarding AI development and usage. First (a) water resource consumption, especially “gray water” resulting from the hardware-cooling processes in data centers, including ethical and responsible approaches when establishing such centers in water-scarce locales (Azarifar et al., 2024). Secondly, (b) efficient electricity usage and the shift toward sustainable models (Zhuk, 2023: 933–938), particularly through “smart grids”. That is, digitalized power networks geared toward maximizing efficiency and sustainability in electricity supply, often entailing strategic placement of data centers in cooler regions to reduce energy demand for equipment cooling and promoting energy transfers among centers to optimize consumption. And finally, (c) the creation of circular-economy frameworks for adequately managing e-waste generated by data centers and AI development labs (Sovacool, Monyei & Upham, 2022: 17).

A key reference for understanding the EU’s perspective on these AI-related problems—before the AI Act—can be found in the so-called European Green Deal (Hainsch et al., 2022: 239). In a broad sense, and with particular relevance for AI as discussed below, the European Green Deal was indeed an ambitious EU plan aimed at tackling the global climate crisis and achieving a sustainable, "climate-neutral" economy. Climate neutrality, in this sense, meant mitigating 100% of the pollution incurred by European society's routine activities by 2050. This plan, inherently complex, sought to align and synchronize changes across energy, industry, agriculture, and consumption. Within that framework, AI played a fundamental role, thus foreshadowing the regulatory discussion on the intersection of AI and environmental concerns.

The European Green Deal's central objective was to attain net-zero greenhouse gas emissions by fostering renewable energy sources, including solar and wind power, modernizing electricity networks, and enhancing energy storage capabilities for locations or periods with lower solar irradiation. In this context, some authors (Kougias, Taylor and Kakoulaki, 2021: 5) stress the particular relevance of photovoltaic infrastructure for certain regions aiming to advance their solar energy transition. The European Green Deal likewise emphasized promoting a circular economy through waste reduction and transitioning away from energy-intensive industries—an aspect that would also affect AI-related e-waste, as explained further on. Specifically, the European Union formally acknowledged the socioeconomic repercussions of so far-reaching a transformation, instituting the so-called Just Transition Mechanism (hereinafter, the "JTM") to offer financial support to the communities most impacted. Some scholars (Sikora, 2021: 547) underscore the central role of this economic and social dimension in the broader environmental measures, as discussed below. The JTM is a new financial instrument under the EU's cohesion policy, intended to back territories facing serious socioeconomic challenges stemming from the transition to climate neutrality. It would subsequently facilitate the European Green Deal itself, which aims to establish a climate-neutral EU by 2050.

Some scholars have criticized the European Green Deal for being excessively "Eurocentric," pointing out that, notwithstanding the JTM, it lacks a worldwide perspective on systemic change (Almeida et al., 2023). One might also question whether it truly falls to the EU to carry out and finance such an extensive global undertaking. Along similar lines, Leonard et al. (2021) suggest that the European Green Deal, somehow "cleans up" Europe by importing energy from countries whose governments presumably do not implement comparable measures, thus revealing what they view as inherent weaknesses in the European energy framework.

As for the European Green Deal's influence on AI, it is indeed present, though not exactly as many might have anticipated. AI is primarily understood as a tool for optimizing the social and production goals set forth in the European Green Deal (Asnaz, 2024: 685). In this vein, some authors (Koundouri, Devves and Plataniotis, 2021: 744–751) explain that the environmental role envisaged for AI under the Europenan Green Deal largely focuses on three aspects: (a) predictive analytics for consumption cycles, (b) optimization of systems to either reduce energy consumption or enhance productivity without increasing it, and (c) enabling better decision-making for policy-making and green finance. Meaning that even if pollution continues, frameworks would be designed to alleviate any intrinsically harmful effects. In essence, the emphasis lies in harnessing AI to lessen pollution, rather than curbing pollution generated by AI itself.

Yet, other authors (Corrigan and Lucaj, 2020 :8) warn that using AI to serve these otherwise commendable ends may involve ethical—and notably environmental—risks, given that the European Green Deal seems to treat AI solely as a planning device to enhance processes for better environmental efficiency, overlooking that AI itself entails considerable environmental costs. A study commissioned by the European Parliament's Special Committee on Artificial Intelligence in a Digital Age (AIDA) reached essentially the same finding (Gailhofer et al., 2021: 30), concluding that applying AI to streamline processes can constitute a double-edged sword. Accordingly, the AI Act integrates a set of measures addressing these concerns.

One significant hazard flagged in the cited report is the high energy consumption of AI systems, particularly those reliant on advanced deep learning architectures—commonly referred to as Large Language Models (LLMs). Rilling et al. (2023) highlight several ethical considerations related to these models in environmental contexts. Strictly speaking, these systems are designed for complex natural language processing (NLP) tasks that demand (a) a protracted, resource-intensive training phase and (b) an equally intensive cloud-based maintenance stage in data centers. Global data centers are anticipated to represent up to 8% of total carbon emissions worldwide by 2030 (Cao et al., 2022: 895), largely due to expanding AI usage. As regards model training, a single LLM such as GPT-3 can consume approximately 700,000 liters of fresh water (Li et al., 2023: 2), and training a 175-billion-parameter model may use about 1,287 MWh (megawatt-hours) of electricity, emitting around 552 metric tons of CO_2 (Patterson et al., 2021: 7). This is, utilizing AI as a “green planning” instrument can itself be counterproductive.

Another key issue addressed in the same report is the growth of e-waste tied to AI. The rapid obsolescence of the hardware required for both training AI and making it available in the cloud, paired with insufficient recycling strategies, could expand global e-waste by as much as 1.2 to 5 million tons by 2033 (Wang et al., 2024: 19). While attributing all such growth exclusively to AI would be misleading, it could nonetheless pose ethical quandaries concerning the “export” of e-waste to countries with fewer resources.

Reflecting on the clear limitations of the European Green Deal—including its handling of AI’s environmental risks—the European Commission published its White Paper on Artificial Intelligence a mere year later. Ulnicane (2022) notes that this paper explicitly addresses water and energy consumption and e-waste generated by AI, topics that had not been explicitly considered in the European Green Deal. Consequently, one might say that it was not the European Green Deal, but rather the White Paper, that heightened awareness of AI’s environmental footprint (touching on both energy and water consumption, as well as hardware life cycles). Certain critics simultaneously argued that an overly cautious stance by the European Union toward AI might hamper innovation and technological advancement (Lilkov, 2021:168–172), even for socially beneficial ends.

Ultimately, the White Paper contends that Artificial Intelligence can and should help realize the goals of the European Green Deal, but must do so in a sustainable manner throughout all phases (Bolón–Canedo et al., 2024: 7)—namely training, fine-tuning, and cloud-based deployment—so as not to undermine the very objective of environmental conservation. From that point onward, the EU seems to fully acknowledge the environmental and sustainability challenges that legal scholars have repeatedly underscored, particularly concerning water usage, energy consumption, and e-waste generation. Indeed, the official document explicitly states that *“Given the growing importance of artificial intelligence, it is necessary to take due account of the environmental repercussions of AI systems throughout their life cycle and supply chain, for example regarding the use of resources for algorithm training and data storage”* (European Union, 2020: 3).

II. GREEN AI AND THE ENVIRONMENTAL PERSPECTIVE IN THE AI ACT

The environmental outlook on AI development and usage (commonly referred to as Green AI) is gaining its own standing in scholarly debates (Rivero Silva & Chinarro Vadillo, 2024: 3). Consequently, it appears that key issues—such as the handling of gray water or efficient energy consumption—are being distanced from the often-cited ‘ethical perspective’ and evolving into an independent approach to AI. In this regard, it is worth highlighting certain AI tools like DestilBERT (Sanh, 2019), CHANO (Rivero Silva & Chinarro Vadillo, 2024), or TinyLlama (Zhang et al., 2024), which incorporate an environmental vision from the outset. That is, they seek optimal energy efficiency without forgoing a reasonable level of performance.

Green AI has been extensively addressed by scholars (Schwartz, 2020: 56 - 61), though it has been only sparsely developed by European lawmakers. This is significant, as Green AI should by nature be inseparable from this emerging and standalone environmental perspective, focusing specifically on efficiency and sustainability strategies throughout every stage of AI model development and public availability. Along these lines, the importance of transparency and standardization in measuring the overall environmental impact and energy consumption involved in creating AI solutions has been underscored (Henderson et al., 2020). Essentially, Green AI has two facets: (a) minimizing the environmental impact during AI generation (training, data loading, and fine-tuning for specific NLP tasks), and (b) mitigating the environmental impact while the model is running in the cloud, assisted by a data center. The following section focuses on the latter format; for now, we concentrate on the first one. By "NLP task," we refer to a specific task that an AI system can understand and that is intended by a human operator, such as translation, identifying color patterns, or generating responses.

Regarding point (a), we can highlight three main techniques: (a1) knowledge distillation, (a2) pruning, and (a3) deep compression. Bucilua et al. (2006: 535) were the first to propose model compression for transferring knowledge from a large model—or an ensemble of models—to train a smaller one without a significant drop in accuracy. Later on, this was formally popularized as the knowledge distillation technique, following the publication by Hinton, Vinyals y Dean (2015: 3). This system involves transferring "knowledge"—defined as the dataset with which it was trained—from a large AI model to a smaller, more efficient model. Such a transfer is effected by incorporating the probability distributions of outputs from the master model (usually referred to in scholarship as the teacher or "parent" model) into the training of the student model. The main goal is to achieve a neural network with fewer parameters that can retain much of the original model's performance. In other words, a connection is established between the teacher model and the student model so that all generic, irrelevant knowledge is discarded, keeping only what is needed for the student model's specific purpose. The challenge is, therefore, how to pass knowledge from a large teacher model to a smaller student model. Essentially, a knowledge distillation system comprises three key components: the knowledge itself (refined dataset), the distillation algorithm, and the teacher-student architecture that allows the transfer of the refined dataset.

For instance, there is no sense in a model designed for computer programming to know the recipe for the Latin American tres leches cake, thus reducing both the dataset size (the body of data comprising the model's knowledge) and the training time. In short, the objective is to avoid broad, generic datasets and load only the strictly necessary data that the AI model will truly require for its designated NLP task. The authors cited above demonstrated that a pre-built ensemble of ten neural networks attained a 19.7% phoneme error rate, whereas a student model trained via distillation reached a 20.5% error rate. Despite a minor 0.8% degradation, the student model was substantially smaller and more computationally efficient.

Meanwhile, the technique known as pruning seeks to reduce neural network complexity by removing weights deemed irrelevant. Han, Pool, Tran y Dally (2015) laid the groundwork for this approach, which is particularly useful in AI transformer-type models developed by Vaswani et al. (2017), publishing “Attention Is All You Need.” That paper is regarded as a historical turning point in AI research, especially in the field of Natural Language Processing (NLP), due to the introduction of the transformer neural architecture—revolutionizing the way modern language models are built and trained.

Transformer-based neural networks function much like sieves: each model “attends” when it receives a specific keyword or concept, ignoring the remainder of the input. Thus, if a model is not intended to address cooking, is it logical for it to include neural network nodes that pay attention to cooking-related input? The procedure may be carried out post-training—removing small-magnitude weights that do not recur frequently—or even at the start of training (Frankle et al., 2021: 5), starting with a more compact neural topology. Transformers, exceptionally effective in processing natural language, are the true engine of large language models (LLMs). Their efficiency and scalability have facilitated the development and training of LLMs with billions of parameters. These techniques not only speed up input-output inference for generative results but also curb the model’s energy consumption—an essential factor in large-scale production environments. Molchanov et al. (2017: 6) presented promising findings in this area. Moreover, the “lottery ticket hypothesis” proposed by Frankle & Carbin (2019) suggests the existence of “winning sub-networks” that, when trained from a common starting point, can retain the entire model’s performance while using 20% or even more fewer parameters across diverse neural architectures.

More recent perspectives on transformers have emerged as well. One example is Tarzanagh et al. (2024: 19), which draws a formal connection between the transformer architecture and support vector machines (SVM), a classic machine-learning algorithm, by focusing on separating and selecting optimal tokens within a sequence. These insights contribute to a better theoretical understanding of transformers and may inspire fresh architectures and training methods.

Finally, deep compression techniques (Han, Mao & Dally, 2015) integrate quantization and intelligent encoding—referred to by some as green coding (including the well-known Huffman coding)—building on the idea of reducing model size by limiting interactions among the model's neuronal connections (commonly called "weights") to find the efficiency curve. It identifies values that rarely appear in the model's output while preserving those more likely to occur. Essentially, this entails lowering the precision of output generation and input analysis up to the point where such a reduction begins to become significant or compromise the model's overall integrity. By decreasing the precision of weights—for instance, from 32 bits to 8 bits—less memory is needed for training, and less bandwidth is required to run the model. Although this approach may cause a slight drop in accuracy, in many cases the performance loss is minimal compared to the efficiency gains. The previously mentioned authors, Han, Mao & Dally (2016), achieved up to a 49x compression ratio in networks like AlexNet and VGG-16 only a year after presenting their original approach, with under a 0.4% loss in accuracy.

In conclusion, given that (a) after issuing its White Paper, it seems the European Union recognized the growing need to gear the development of complex AI models—LLMs in particular—toward Green AI solutions, and (b) legal scholarship has identified three highly specific strategies to implement in developing such models, it was anticipated that the AI Act would indeed incorporate some of these concrete, effective measures for mandatory compliance by AI developers, at least for general-purpose models. Some authors have observed that the AI Act is surrounded by a sort of mythical aura, as if it were a panacea for all AI-related issues in Europe, whereas in truth there are positive elements but also numerous shortcomings or ambiguities (Veale & Zuiderveen Borgesius, 2021: 98 – 105). In this context, it is also appropriate to acknowledge that, albeit subtly, the AI Act demonstrates an emerging interest in assessing the energy consumption of artificial intelligence systems. Environmental considerations are thus incorporated in a secondary and voluntary manner (Tu & De Castro e Silva, 2025: 20). According to Annex XI (related to Article 53(1)(a)), when direct data on an AI system's energy consumption is not available, it may be estimated through alternative means. In other words, for the first time, energy consumption—an issue of central importance in the context of Green AI—is recognized as a relevant factor that general-purpose AI providers should account for in order to comply with the legislation. It would have been valuable for the Act to distinguish between the energy used during training and that consumed during deployment, but this nonetheless represents a significant and promising first step.

The AI Act distinguishes between three types of AI models and associates specific safeguards with each category. First, there are models that engage in prohibited practices as outlined in Article 5, which do not incorporate any environmental considerations. Second, so-called "high-risk" AI models, defined in Articles 6 and 7, are subject to the assessment obligations set forth in Title III of the regulation. Although these provisions do not include explicit environmental measures, Recital 48 opens the possibility that violations of the EU Charter of Fundamental Rights could serve as grounds for classifying a model as high-risk. Given that Article 37 of the Charter explicitly refers to environmental protection as a fundamental right, it could be inferred that particularly polluting AI systems might, at least indirectly, fall within this category. Nevertheless, some scholars argue that there is currently no objective way to assess such environmental risks (Kusche, 2024: 2).

Finally, the third category includes "low-risk" AI models, which are subject to limited transparency obligations set out in Title V, applicable in specific cases such as the identification of deepfakes or realistic conversational agents. Beyond these requirements, such systems are primarily governed by voluntary codes of conduct. Yet, even so-called low-risk AI can have significant environmental impacts, particularly due to its high energy demands and carbon footprint (Pagallo, 2025: 5–7). In short, many environmental risks and the protection of related rights may still fall outside the scope of the Act's definitions.

Ultimately, it can be said that through the AI Act, the European legislator conducted an in-depth risk assessment related to AI development, —albeit within an environmental paradigm that is present, yet not concretely articulated. Accordingly, Article 1 of the regulation stipulates as one of its objectives, among others: the *“protection of the environment against the harmful effects of AI systems.”* Likewise, Article 3(49) defines a *“serious incident”* as one that causes environmental damage. Similarly, Article 95.1(b) states that a key principle within the voluntary code of conduct shall be “*the assessment and minimization of AI systems’ environmental sustainability impacts, including energy-efficient programming and techniques for designing, training, and using AI in an energy-efficient manner*” (European Parliament and Council of the European Union, 2024: 113). Based on the aforementioned scholarly discussions, this means that environmental factors would include analyzing energy consumption, carbon footprint, the use of natural resources (especially water and minerals), e-waste generation, and any other relevant environmental impacts throughout the AI system’s life cycle. Next, to continue the work set out in the AI Act, metrics and indicators would be needed to quantify environmental impact, such as the energy consumed during training depending on the AI model and the volume of data processed, along with parameters that affect the hardware’s lifespan. Algorithms aimed at minimizing energy consumption and computing resources would also be required—ultimately seeking AI architectures that are inherently more efficient, optimizing the training process through smaller models with fewer parameters, as well as model compression techniques to significantly reduce energy usage.

Additionally, since article 10 of the AI Act provides for standardized data-sharing requirements prior to placing “high-risk” AI models on the market, article 40.2, in conjunction with article 10, stipulates that *“the request for documents on the processes for submitting information and documentation to improve resource-related performance of AI systems, such as reducing energy usage and other resource consumption by high-risk AI systems throughout their life cycle, as well as energy-efficient development of general-purpose AI models,”* must be included among those shared documents. In line with that provision, article 112.6 of the same regulation states: *“By no later than August 2, 2028, and subsequently every four years, the Commission shall present a report reviewing the progress in drafting standardization documents on the energy-efficient* *development of general-purpose AI models and shall assess the need for additional measures or actions, including binding measures or actions. This report shall be forwarded to the European Parliament and the Council and shall be made public."* (European Parliament and the Council of the European Union, 2024: 76).

Some commentators note (Pagallo, 2025: 5) that while Recital 27 of the AI Act highlights the need to develop AI systems that uphold environmental responsibility and serve the common good, the concrete commitments to environmental protection remain vague. Shortly after the initial draft was introduced in 2021, the AIDA committee criticized the proposal for neglecting serious ecological risks—an omission that suggests that, despite rhetorical references to sustainability, the Act's mechanisms for addressing environmental harm lack binding obligations. Critics argue that (a) this approach falls short of enforcing genuine accountability for ecological impacts and that (b) it results in a de facto delegation to technical experts regarding the acceptability of specific AI models (Laux, Wachter & Mittelstadt, 2024: 4), a dynamic that may ultimately undermine both the credibility of the AI Act and public trust in AI technologies more broadly.

In relation to the above, other authors (Pagallo et al., 2022: 4) had previously examined the AI Act's draft, cautioning that the provisions on "high-risk" are confined to scenarios posing threats to human health, safety, or fundamental rights, thereby overlooking potential ecological damage. For instance, Articles 5 and 6 neither address biodiversity loss nor greenhouse gas emissions unless they result in a direct human impact. This perspective is shared by other authors (Melikidou, 2025: 38) who argue that the drafting largely overlooks environmental protection, focusing instead on human-centered concerns such as safety, rights, and livelihoods in its risk-based assessment of AI systems. Environmental risks are mainly addressed when they directly impact human interests, revealing a limited scope.

Be that as it may, it is worth noting that the Article 47 of the AI Act allows for compliance exceptions, insofar as Member States may — in exceptional cases — deviate from the standard framework and impose more (or less) restrictive measures for the protection of the environment. However, some authors (Smuha et al., 2021: 47 - 48) argue that the exception clause granted to Member States under the AI Act Proposal—allowing them to deviate for reasons such as environmental protection, is overly broad and lacks sufficient clarity. They warn that such ambiguity could lead to unjustified infringements of fundamental rights, especially considering that many high-risk AI systems are operated by state authorities themselves. Consequently, the power to exempt their own systems from regulatory safeguards may create incentives for potential abuses of power, unless more robust constraints and clearer criteria are introduced.

In sum, one may conclude that the AI Act has indeed acknowledged the existence of an environmental and sustainability issue linked to the creation of AI solutions. Moreover, it recognizes that energy usage and other general resources must be a genuine concern when building AI solutions. Nonetheless, in my view, these brief and rather generic legal provisions cannot be seen as a distinctly environmental or Green AI approach in the strict sense. Thus, without prejudging the EU's stance on the matter, it appears the Act aims to project a "green" image without incorporating practical, concrete measures in the text. This practice could reasonably be construed as insufficiently transparent on the part of the administration vis-à-vis the regulated community, evoking Zehner's (2012) famous concept of green illusions—the mistaken belief that renewable energies alone would represent an ethical and environmental panacea.

Why might the AI Act be labeled a green illusion? Simply because it repeatedly asserts that environmental protection—and specifically addressing AI's harmful effects—is a priority of the regulation, yet it establishes no truly concrete measures to implement Green AI strategies like those described earlier. Nor does it provide any immediate mechanism to curb indiscriminate training with superfluous data for a given NLP task or to practically enforce any standard of environmental sustainability. Indeed, prioritizing technological development over its detrimental environmental impacts is a perfectly defensible position, and it has been supported by some of the scholars mentioned previously. What is even harder to justify, however, is maintaining that stance in practice while simultaneously, through legislative measures, endorsing the opposite. .

In this vein, recent scholars (Alder et al., 2024) noted that a critical examination of the AI Act cannot ignore the obvious "gap" concerning indirect greenhouse gas emissions from AI applications and the absence of a standardized method for exchanging information that, at some point, will likely emerge between authorities and developers. Hacker (2024: 2) similarly argues that the AI Act could be substantially improved in terms of environmental protection, particularly by making it more comprehensible and specific. Clearly, the AI Act focuses on other types of risks—certainly significant ones—but sidelines the environmental perspective, leaving it without a clear, enforceable framework for national authorities and developers. In this same context, Members of the European Parliament such as Eero Heinäluoma have recently criticized the European Commission for relying on developers' voluntary disclosure of training data, describing it as improbable or untrustworthy (European Parliament, 2024). This point has a critical impact on an AI system's environmental perspective, given that model size and the training and fine-tuning duration are key factors for measuring environmental impact. Without standardized, reliable access to these data, it is impossible to determine whether a given AI contaminates more or less.

Similarly, as we have seen, the AI Act employs a terse phrase—"*energy and other resource consumption*"—to describe the e-waste challenge, along with its exportation to developing countries and the gray water generated by hardware cooling, all of which we have touched on elsewhere and which pertain to reducing environmental impact during AI model operation. This directly involves data centers, a subject we address below. Specialized scholarship has extensively explored data centers as a major environmental sustainability concern for AI, and one that is not strictly connected to its training phase (Ebert et al., 2024: 4). Likewise, Members of the European Parliament such as Spain's Nicolás González Casares have voiced apprehension that the AI Act disregards the energy demand of these data centers, which could potentially double between 2022 and 2026 (European Parliament, 2024).

III. AI LABELING AND SELF-REGULATED TRANSPARENCY AS A "DE LEGE FERENDA" PROPOSAL FOR AMENDING THE AI ACT

The reality of AI as a top-tier consumer of energy resources and a producer of CO2 emissions—principally due to large-scale training of LLM models associated with increasingly complex NLP tasks—seems beyond dispute. In this regard, it is indeed striking that despite being well-documented by scholars (Liu et al., 2022), as well as referenced in the European Commission's *Communication: Shaping Europe's digital future* (2020: 6), the AI Act does not, in my view, adequately address the matter, relegating environmental considerations to a mere expression of concern without offering any concrete short-term measures to resolve the issue.

Calls for measures aligned with the so-called Green AI, mentioned above, have proliferated since 2019, when Schwartz, Dodge, Smith, and Etzioni introduced the term and contrasted it with what the scientific community calls Red AI. In other words, there has been an ongoing race to achieve higher scores on benchmarks—standard tests used to measure AI models' capabilities—regardless of cost (Dhar, 2020: 423–425). Essentially, this competition to create ever larger AI models with ever more knowledge has led to unsustainable computational, energy, and water demands, which underpins the core of Red AI. This point is key: AI, *per se*, is not necessarily environmentally unsustainable; rather, it is the Red AI perspective that frequently entails this unsustainable factor. In any event, scholarly commentary is largely unanimous in maintaining that leveraging AI for process and system efficiency improvements—precisely the aim of the European Green Deal—cannot occur without acknowledging and addressing the ethical and environmental challenges associated with extensive use of this technology (Coeckelbergh, 2021: 68–70).

Within this broader clash between the Red AI perspective embraced by developers and the Green AI perspective espoused in academia, the AI Act's ambiguity in recognizing environmental risks has prompted a range of reactions. Particularly noteworthy is the energy sector's concern, given that the regulation does not clearly reveal how the European Union intends to reduce or make AI's electricity consumption more efficient, creating uncertainty in financial and investment terms (Apráez & Noorman, 2024). In this regard, certain authors observe that in the midst of a clear energy transition, especially one oriented toward "green" systems, clarity about the growing computational and energy demands of AI is vital for the industry's proper and sustainable development (Heymann et al., 2023).

This lack of specificity on the EU's part, when formulating the AI Act, is hardly accidental. Moreover, while the AI Act was being finalized, the European Commission was simultaneously seeking experts to measure AI's impact on CO2 emissions (European Comission, 2024). Hence, it is not that the European Union is unaware of AI's environmental risks—indeed, the European Green Deal already confirmed an understanding of these issues—but rather that, despite this awareness, the EU has been either unable or unwilling to be sufficiently precise about what measures it plans to implement to address the problem.

In line with the above, it is worth noting that the European Commission (2021) has introduced a community-financing project called Horizon Europe, initially planned to run until 2027 and aimed precisely at these matters. Under Horizon Europe, three research initiatives have been launched to explore Green AI approaches for the development of AI in Europe: (a) SustainML, (b) dAIEDGE, and (c) ELIAS (European Parliament, 2024). The fact remains, however, that little information is publicly available regarding these projects' environmental sustainability outcomes.

Against this background, by way of a "de lege ferenda" proposal, we present two key amendments to strengthen the AI Act's specificity—each focusing on a different sub-dimension of Green AI. The first concerns the training of AI models; the second concerns making them publicly available through the above-mentioned data centers and the more or less sustainable way in which these centers operate. We will further expand on the latter proposal below. First, it is essential to explain that the concept of benchmarking is closely tied to the previously discussed notion of Red AI. Each of the general-purpose AI models has been fiercely competing to outperform rivals on a very limited set of benchmarks. Certain authors' studies reflect a lack of variety in these benchmarks and in the metrics they use to assess different AI models (Bowman, 2021: 6).

Ultimately, this "benchmark fever" drives entire teams of LLM developers—out of sheer pride, as well as the promotional interests of their respective corporations—to tweak algorithms or datasets purely for the sake of surpassing competitors in the usual public benchmarks. That said, other authors have noted that the current set of general-purpose benchmarks, whether by design or oversight, often contains loopholes in their evaluation methods, thus undermining the final results of a model's performance assessment (Zheng et al., 2024: 8). Along similar lines, yet another segment of the academic literature advocates best practices to avoid making one's AI model a "benchmark cheater" that exploits such flaws. In other words, it cautions against maliciously fine-tuning an LLM solely to pass predictable questions in a particular benchmark, rather than genuinely refining it for a specific NLP task (Zhou et al., 2023: 7).

What we propose is simply the inclusion of an energy cost factor—and environmental impact more generally, in keeping with Green AI policies—as a negative factor that reduces a model's performance score in the aforementioned general-purpose benchmarks. By doing so, we seek to introduce a paradigm whereby disproportionate use of energy and water resources might be viewed as a form of "unfair competition," or, put differently, as poor practice in AI development. The objective is for Green AI methods (e.g., pruning, deep compression, and knowledge distillation) to be embedded from the outset during AI model training. This approach could also reassure certain Members of the European Parliament, such as Andreas Schwab, who have raised concerns about potential cartel-like or oligopolistic behavior by some leading AI solution providers (European Parliament, 2024).

Conversely, other MEPs—among them the aforementioned Andreas Schwab and Brando Benife (European Parliament, 2024)—point out that, despite article 53 of the AI Act establishing a limited exchange of information, opacity remains the norm among AI model developers, and there is still no standardized measurement system that, at the same time, can protect trade secrets of the corporate entities behind these development teams. Likewise, the absence of a standardized information system makes it evidently difficult to compare AI models. Although the solution this paper proposes calls for the benchmarks themselves to institute ad hoc measurement schemes, the lack of clarity in the Act can be deemed a legitimate criticism.

This is without prejudice to the fact that, under article 56 of the AI Act, the EU AI Office is expected to draft a Code of Conduct for so-called general-purpose AI (GPAI), yet the European Parliament still lacks any details—even as to who the expert panel members will be (European Parliament, 2024). Thus, in a setting where scholars highlight that lack of transparency is a major problem for these benchmarks (Daneshjou et al., 2021: 1362–1368), it remains to be seen how the European Union will effectively mandate that transparency.

A straightforward, if somewhat liberal, response to this problem is that such a complicated issue—specifically, in this area—should not, in my view, be handled via specialized legislation promoted by the EU. Especially in light of certain authors' observations pointing to a sort of overregulation (Brownsword, 2019) of a matter that does not require more rules, but rather greater specificity on points that, regulation after regulation, remain unaddressed: for instance, e-waste management, handling of gray water contaminated after its use in cooling data centers, and mandatory Green AI strategies in general-purpose AI solutions. Therefore, in an attempt at a self-regulatory approach, it would be advisable for the benchmarks themselves to institute internal review and evaluation systems—akin to how e-commerce entities do so under Directive 2000/31/EC. Soft-law strategies within a self-regulation framework have proven effective in other areas marked by regulatory complexity.

This arrangement would allow competition not only among developers but also among the benchmarks themselves, who would highlight their environmental impact metrics—and, ideally, the practice would become an industry standard. At a minimum, the parameters laid out by Strubell, Ganesh, and McCallum (2020) should apply. These consist of (a) the carbon intensity of the energy mix, i.e., the type of energy available in the geographic region where the model is trained—since the ratio of fossil fuels to renewables can hugely impact the environmental footprint of a training session; (b) the type of hardware utilized for training (GPU, TPU, or multicore CPU) and its energy efficiency, which directly influence the kWh consumed per hour of training; and (c) whether “best practices” for Green AI, such as pruning or transfer learning (teacher–student model), were employed.

In the end, the aim is to capitalize on this “benchmark fever” so that development teams, in their obsession with showcasing a superior record on general-purpose benchmarks, implement environmental sustainability measures from the outset—which would, at least initially, be evaluated on a self-regulated basis. The constructive competition among benchmarks seeking more accurate measurement methods and among developers striving to adhere to them and score better, in my view, represents the crux of our first proposed amendment to the AI Act.

Finally, as a second major proposal, it would be worthwhile introducing a labeling system—one that must be both put into practice and disclosed to consumers, whose purchasing power ultimately drives the financing of these systems. While the foregoing benchmarking measure was aimed at development teams, this second measure targets the sales and marketing arms of major AI providers. As previously noted, Green AI includes strategies to ensure the data centers on which AI systems depend for their operation achieve the highest possible efficiency.

Consequently, the premise here is that end users of AI systems should be aware if they are using a model that is especially polluting in its cloud phase, and to what extent it is polluting. In that regard, “green marketing” scholars (Ottman, 2011) have already noted the commercial benefits associated with projecting a “green” image and the fact that, to a greater or lesser degree, we are all “green consumers,” which will inevitably affect how licenses for large LLMs are marketed. Thus, the aim is likewise to bring competition among AI model vendors into the “marketing fever,” competing over who can design a more energy-efficient cloud platform.

Such labeling should indeed be grounded in some code of conduct endorsed by the European Union in collaboration with experts in the field. It would concentrate on the cloud system and address one of the major concerns in the literature regarding AI: namely, what happens within the data centers that accommodate the hundreds of thousands of user queries AI models receive each day. In my view, a self-regulatory framework akin to what was mentioned earlier could keep this labeling “alive” and up to date, adapting it to new AI generations featuring novel complexities (e.g., quantum computing). Mere regulation is prone to becoming “dead letter” shortly after a cutting-edge technology emerges.

In this context, some authors (Nassar, 2025: 26) point out that, within the European Union, data centers consumed 124 TWh of energy in 2018. Furthermore, a 28.2% rise in energy consumption is projected by 2030 compared to 2018 levels—potentially representing about 3.2% of the EU’s total electricity demand. Similarly, others (Zhu et al., 2023: 17) warn that by 2023, data centers may have produced anywhere from 2% to 4% of worldwide carbon emissions.

Scholars generally identify three main shortcomings in current data centers intrinsically tied to AI, which should be addressed by the proposed labeling: (a) inefficient energy use, (b) substandard hardware life-cycle management, and (c) inadequate cooling strategies. Beloglazov (2011: 50) suggests that the primary solution to (a) is dynamic consolidation of virtual machines, thereby reducing the power consumed by idle servers and optimally assigning resources. Essentially, this means running multiple virtual machines or servers on a single hardware unit, thus decreasing energy consumption—hosting multiple operating systems (software) on one CPU, provided that CPU can handle the load, rather than using multiple CPUs and increasing electricity and water usage for cooling, as well as e-waste. Similarly, Wang et al. (2022: 162–168) propose a comprehensive “green data center” framework that entails adopting renewable energy, using indicators such as PUE or WUE (efficient cooling systems), and redesigning infrastructure to minimize thermal loss. Particularly noteworthy is placing data centers in cold regions to exploit natural temperatures and using high-performance cooling chemicals rather than water-based systems, which generate large volumes of so-called “gray water.” These are waters used for cooling data center hardware which, once used, become contaminated and unfit for human consumption or irrigation, with seepage into the ground posing health hazards (Liu & Chang, 2024).

Moreover, electronic waste accumulation remains a critical issue for data centers—especially those located in developing countries that lack recycling systems for outdated servers. Other authors (Kiddee, 2013: 1240–1245) observes that for nearly a decade, we have struggled with the absence of phased renewal plans and inadequate disposal of electronic components, which often pollute soil and water sources by leaching heavy metals. The solution calls for implementing hardware life-cycle management protocols, ensuring device traceability, and promoting reuse and recycling.

Consequently, if an AI model runs on more efficient, less polluting servers—referred to in scholarship as *green data centers* (Jin et al., 2016: 4)—the user could make an informed choice in a market that, as noted earlier, tends toward oligopoly. Hence, both environmental benchmarking and environmental labeling emerge as clear and tangible proposals that I hereby lay out *de lege ferenda*. The hope is that, at some point, a future amendment to the AI Act might adopt them, thus addressing the scholarly criticisms regarding the Act’s uncertainty and limited effectiveness in this domain.

It is also worth briefly highlighting the use of quantum computing, which—with its exponentially higher processing capacity compared to classical computing—shows immense potential for revolutionizing Green AI, even if it remains in an early stage at the moment. As is well known, training large AI models consumes vast amounts of energy. Quantum algorithms could streamline this process, reducing both training times and computational resource needs, and thereby drastically cutting the carbon footprint. Specific examples include companies like Zapata AI, which employs quantum algorithms to compress LLMs and thus significantly reduce training energy requirements, and Google Quantum AI, which is investigating how quantum computing can optimize AI algorithms and foster more energy-efficient AI hardware designs. It’s opinion of the authors that, in the future, Green AI will be complemented with the aid of this new technology.

IV. CONCLUSIONS

The environmental challenges resulting from the growing use of AI reveal a tension between the European Union’s longstanding commitment to environmental protection—rooted in the earliest stages of the TFEU—and the pressing need to regulate a technology whose implications extend far beyond the traditional economic paradigm, which from the outset has also encompassed social and environmental considerations, as stated in Article 11 of that treaty. The European Green Deal, in its quest for a carbon-neutral Europe, recognized the potential of AI as a tool for enhancing energy efficiency and streamlining production processes. Yet it fell short of establishing specific provisions to address the inherent environmental impact of AI in terms of water and energy consumption, as well as e-waste generation.

The rise of AI poses a major challenge for the European Union: reconciling its historical protective vocation, present since the TFEU’s inception, with the necessity of regulating a technology whose ramifications transcend the traditional economic model. In this sense, making accurate and reliable information on the environmental impact of an AI model available to the consumer is imperative.

Subsequent to the European Green Deal, the approval of the so-called AI Act (Regulation (EU) 2024/1689) aimed to remedy the lack of clear provisions addressing AI’s direct environmental impact, setting out reference frameworks to protect fundamental rights and prevent risks, including those relating to the environment. Nevertheless, the final text exhibits tangible shortcomings that restrict its effectiveness. While it does refer to environmental protection as one of its main objectives and acknowledges the possibility of treating environmental breaches as a serious incident, it fails to create a regulatory apparatus with specific, enforceable, and—above all—verifiable sustainability obligations. Instead of imposing binding requirements, the AI Act relies on recommendations and voluntary codes of conduct, accompanied by the promise of a future review report that, in practice, postpones the adoption of executive measures to an uncertain date.

This essentially programmatic approach lacks the force necessary to curb the so-called Green Illusions—namely, environmental rhetoric unbacked by effective regulatory mechanisms. In the field of AI, these illusions arise from the absence of mandatory technical requirements for reducing energy and water footprints, the lack of tools for monitoring the discharge of "gray water" in data centers, and the failure to establish a unified method of evaluating the production and management of electronic waste. The gulf between acknowledging the problem and taking concrete action underscores a predominantly reactive regulatory mindset, that appears more concerned with avoiding barriers to innovation than with setting clear boundaries for unsustainable technology usage.

The *de lege ferenda* proposals advanced in this article precisely reflect the urgency of moving from abstract formulations to tangible mechanisms. The first, involving the inclusion of environmental impact factors in AI performance benchmarks, aims to ensure that energy consumption, carbon footprint, and water usage become evaluation criteria as relevant as accuracy or processing speed. Given how prevalent these benchmarks are in the competitive culture of both the research community and industry, they present an opportunity to redirect efforts toward efficiency and to encourage the use of Green AI methods such as pruning, deep compression, or knowledge distillation.

The second proposal—implementing an environmental labeling system for AI—seeks to instill transparency in the procurement and use of cloud-based services. The goal is to provide end users, as well as investors and regulators, with objective information about the type of data center employed, its energy efficiency, the origin of the energy used, and the level of emissions per operation. This measure would not only enable users to distinguish providers genuinely committed to sustainability but could also spur responsible environmental competition in a market increasingly dominated by large cloud-service providers.

Furthermore, it is worth highlighting the emergence of promising technological breakthroughs such as quantum computing, which has the potential to accelerate Green AI solutions, making them more sustainable and efficient across various domains, from renewable energy to precision agriculture. Monitoring the evolution of this technology will be essential for future proposals.

In short, the AI Act has fallen short in its ecological dimension, limiting itself to a formal acknowledgment of risks without establishing clear obligations or strict deadlines for adopting solutions. Self-regulation or the future development of codes of conduct will not be sufficient to address the magnitude of the issue unless real incentives and sanctions are introduced. Consequently, this paper advocates the need to rethink the regulatory framework—through amendments or new legislative guidelines—to integrate Green AI requirements at every stage of AI development and deployment. By doing so, the EU could demonstrate consistency between its globally recognized leadership in environmental discourse and its actual regulatory practice concerning a technology as pivotal to the future as AI.

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