

THE NET IMPACT OF ARTIFICIAL INTELLIGENCE ON THE ENERGY TRANSITION

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Abstract

This article examines the net climate impact of artificial intelligence in the energy transition. The study is conceptual and is based on a structured narrative review of scientific literature and institutional documents published between 2020 and 2026. Drawing on the contributions reviewed, it proposes a counterfactual accounting framework that compares total emissions associated with the use of artificial intelligence with the emissions estimated for a situation in which the technology is not used. The change in emissions is decomposed into four components: emissions from digital infrastructure, changes arising from the scale and structure of production, demand rebound effects, and emissions avoided through efficiency gains. The framework is applied to Romania’s industrial sector through three sensitivity scenarios, using official data for 2024. Depending on the share of industrial electricity consumption affected by AI applications and the assumed reduction in energy use, the results indicate annual electricity savings ranging from 5.121 to 136.562 GWh and avoided operational emissions ranging from approximately 963 to 25,674 t CO₂e. These values are conditional on the scenario assumptions and do not represent savings already achieved. The results show that reducing energy use per unit of output does not guarantee a reduction in total emissions, because the net climate benefit also depends on the footprint of computing infrastructure, changes in output, and rebound effects.

Keywords: artificial intelligence; Energy transition; energy efficiency; industry; rebound effect; net emissions.

JEL Classification: O33, Q42, Q54, Q56.

1. Introduction

The literature examines the influence of artificial intelligence on the energy transition both through applications that can reduce energy use and emissions and through the resources required to develop and use AI systems. Rolnick et al. (2022) identify machine-learning applications in electricity generation and distribution, transport, buildings, and industry. In the energy sector, these include forecasting renewable electricity generation, optimizing grid operation, managing demand, and detecting equipment faults. To organize these effects, Kaack et al. (2022) propose three categories: effects associated with computing infrastructure, direct effects produced by the use of applications, and systemic effects generated by changes in economic activity.

The first category comprises the energy use and emissions associated with developing, training, and using models. Henderson et al. (2020) emphasize the need for standardized reporting of the energy use and emissions generated by machine-learning systems. Luccioni et al. (2023) show that assessment results depend on the system boundaries: including the manufacture of equipment and infrastructure, alongside the operational energy required to train and use the model, yields a more complete estimate of the carbon footprint.

According to the International Energy Agency (IEA, 2026), global electricity consumption by data centers could increase from approximately 485 TWh in 2025 to 950 TWh in 2030, when it would account for about 3% of global electricity demand. Over the same period, electricity consumption by AI-focused data centers is expected to triple (IEA, 2026). These estimates concern

data-center electricity consumption and do not include all environmental effects arising throughout the life cycle of equipment and AI systems.

The second category examined in the literature concerns emission reductions achieved in sectors where AI applications are used. Under the IEA's widespread-adoption scenario, existing applications in buildings, industry, transport, and energy could deliver reductions of approximately 1.4 Gt CO₂ in 2035 (IEA, 2025). The IEA notes that this value is the outcome of a scenario conditional on access to data, the availability of the required infrastructure and skills, and the removal of regulatory and security barriers. It therefore does not constitute a forecast of certain emission reductions.

Systemic effects are examined in the economic literature in relation to changes in production and consumption caused by digitalization. Lange et al. (2020) distinguish four mechanisms: direct consumption associated with the production, use, and disposal of digital technologies; savings resulting from increased efficiency; expansion of economic activity following productivity gains; and changes in the sectoral structure of the economy. Their study shows that efficiency improvements can be accompanied by rebound effects when lower costs lead to expanded use and higher total energy consumption. The IEA (2025) likewise includes rebound effects among the factors that can reduce the emission savings attributed to AI applications. Rebound effects and the Jevons paradox in the context of AI are also examined by Luccioni et al. (2025).

Building on these contributions, the study pursues two objectives. The first is to delineate the channels through which AI influences the energy transition: consumption by computing infrastructure, reductions achieved in the sectors of application, and effects at the level of the economic system. The second is to formulate a framework for assessing net impact, comprising four components: emissions avoided through AI use, the direct footprint of computing infrastructure, emissions enabled by AI applications, and rebound effects. These components are assessed against a scenario in which the application under analysis would not have been used.

2. Methodology and conceptual framework

The study is conceptual and is based on a structured narrative review of scientific research and institutional documents published between 2020 and August 2026. This period was selected to capture both the studies that consolidated systematic reporting of the energy use and carbon footprint of machine learning (Henderson et al., 2020) and recent economic analyses of the relationship between digitalization, efficiency, and total energy demand (Lange et al., 2020).

The selection does not claim the exhaustiveness of a systematic review and does not include a meta-analysis. Sources were considered if they established a direct link between AI use, resource consumption, and changes in greenhouse gas emissions. Peer-reviewed articles published in scientific journals were included, along with documents from institutions with responsibilities in energy, the digital economy, and climate policy. A source was considered relevant if it addressed at least one of the following: consumption by computing infrastructure, the effects of applications on energy efficiency, changes in production or demand, and the systemic consequences of digitalization. IEA reports (2025, 2026) were used for the prospective scenarios. For data centers, the indicators established by Commission Delegated Regulation (EU) 2024/1364 were also considered (European Commission, 2024). The review excluded commercial estimates that do not disclose their calculation method, values lacking clear system boundaries, and sources that discuss sustainability without verifiable indicators or methodology.

Existing research delineates the impact of AI in different ways. Kaack et al. (2022) separate the footprint of computing infrastructure, the effects of applications, and changes that propagate through the economic system. The OECD (2022) distinguishes impacts associated with the development, use, and disposal of equipment from the favorable or unfavorable indirect effects of applications. Lange et al. (2020) show that technical efficiency may be accompanied by higher consumption, while Alpine et al. (2026) examine how productivity gains are transmitted among energy-related activities with different carbon intensities.

Based on these distinctions, the study proposes a counterfactual accounting framework for operationalizing the effects. The framework compares the total emissions associated with the same activity when artificial intelligence is used with the emissions estimated for a situation in which the technology is not used.

Climate level: all changes that can be converted into tones of CO₂ equivalent are brought together in a common balance.

Physical level: electricity, water, and materials are reported separately in MWh, m³, and kilograms until documented factors for conversion into CO₂ equivalent are available.

The principal indicator is the change in total emissions associated with introducing the AI application:

$$\Delta GHG(AI) = GHG(\text{with AI}) - GHG(\text{without AI})$$

A negative value indicates an emission reduction; a positive value indicates an increase.

To identify the source of the difference, the total change is decomposed into four terms. The notation and order of calculation constitute an operational tool proposed in this article, while the economic mechanisms they represent are grounded in the cited literature:

$$\Delta GHG(AI) = D + S + R - E$$

Table 1. Operational decomposition of the change in emissions associated with AI use

Symbol	Indicator	Scope of assessment
$\Delta GHG(AI)$	Total change	Difference between total emissions in the scenario with AI and those in the scenario without AI.
D	Digital infrastructure	Additional emissions from equipment, electricity, cooling, cloud services, and component replacement.
S	Scale and structure of production	Change in emissions when AI alters the volume of activity, the technology mix, or the structure of production.
R	Demand rebound	Additional emissions caused by increased use after a reduction in cost or in consumption per unit.
E	Efficiency gains	Emissions avoided by reducing energy use, materials, scrap, or operating time relative to the scenario without AI.

Each term is measured against the same counterfactual scenario without AI. The components must have the same analysis period, geographical scope, unit of measurement, and compatible assumptions about production and the marginal electricity mix. Observed values, modelled estimates, and projections are identified separately and are not added together when their system boundaries do not coincide.

To avoid double counting, the same increase in activity cannot be recorded simultaneously under S and R. The term S is used for changes in the volume or structure of production, whereas R is used only for demand growth induced by lower costs or efficiency gains. If the two mechanisms cannot be separated using the available data, they are reported jointly and this limitation is stated explicitly.

The result must be interpreted together with emission intensity per unit of output. A decline in emissions per unit does not demonstrate a reduction in total emissions when output increases. At the same time, electricity, water, and material use remain physical indicators until they can be converted using documented factors. This separation prevents the aggregation of incomparable units.

Based on these distinctions, the assessment of the climate impact of artificial intelligence is organized at four levels. This structure is an analytical framework proposed in the present study and does not reproduce a pre-existing model.

The first level concerns the efficiency of the AI system, measured by energy use and by the emissions associated with training, inference, or a unit of computation. Considering efficiency alongside model accuracy is consistent with the Green AI approach formulated by Schwartz et al. (2020).

The second level concerns the infrastructure used for computation and includes data-center efficiency, cooling systems, equipment utilization, and the source of the electricity consumed. The third level evaluates the outcome of the application in the domain where it is implemented by comparing energy use or emissions with an equivalent scenario without AI. The fourth level extends the analysis to systemic effects, including growth in the volume of activity, changes in demand, rebound effects, and the transfer of emissions between sectors.

The four levels are not interchangeable. Reducing the energy required for a computational operation does not demonstrate that the application reduces emissions from the activity in which it is used. Similarly, a reduction observed at the level of a factory, building, or grid does not establish the total climate impact without examining changes in the volume of activity and effects generated in other sectors.

Within this framework, Green AI denotes the reduction of resource use and environmental impacts associated with AI systems, whereas the use of AI for environmental goals concerns the effects of applications on other economic activities. Assessing net impact requires both dimensions to be analyzed against the same counterfactual scenario.

3. Scenario analysis for Romania's industrial sector

According to Eurostat (2026a), final electricity consumption in Romania's industrial sector was 17,070.291 GWh in 2024. In the same year, 1.30% of manufacturing enterprises with at least ten persons employed used at least one AI technology (Eurostat, 2026b). The indicators perform distinct functions in the analysis: electricity consumption provides the energy baseline for the scenarios, while the share of enterprises describes the extent of AI diffusion. This share is not used as a share of industrial electricity consumption.

To convert electricity savings into avoided operational emissions, the analysis uses the average emission intensity of electricity generation in Romania, estimated by the European Environment Agency at 188 g CO₂e/kWh for 2024 (EEA, 2025). This is an early estimate based on average national generation and does not represent the intensity of the marginal mix activated at a particular hour. The results therefore provide a transparent sector-level approximation, not a measurement of the marginal effect of each AI application.

Baseline data: industrial electricity consumption, the share of manufacturing enterprises using AI, and the estimated average emission intensity of electricity generation.

Scenario assumptions: the share of industrial electricity consumption affected by AI applications (a) and the reduction in energy use in the targeted activities (r).

Calculations performed in this study: annual electricity savings, avoided operational emissions (E), and the maximum value of $D + S + R$ compatible with a net climate benefit.

Three sensitivity scenarios were constructed; they are not forecasts. The share of industrial electricity consumption affected by AI is denoted by a, while the reduction in energy use in the targeted activities is denoted by r. The values of 3%, 5%, and 8% assigned to r are sensitivity assumptions, and the upper bound is close to the order of magnitude of the energy savings estimated by the IEA (2025) for light industry by 2035 under the widespread-adoption scenario. This reference provides a benchmark for parameterization; it does not demonstrate that the same reduction will be achieved in Romania.

For each scenario s , the calculations are:

$$\begin{aligned} \text{Electricity savings}_s &= 17,070.291 \times a_s \times r_s \\ E_s &= \text{Electricity savings}_s \times 188 \text{ t CO}_2\text{e/GWh} \end{aligned}$$

Table 2. Results of the sensitivity scenarios for Romanian industry, based on 2024 data

Scenario	a	r	Electricity savings	E _s : avoided emissions
Prudent	1%	3%	5.121 GWh/year	963 t CO ₂ e/year
Intermediate	5%	5%	42.676 GWh/year	8,023 t CO ₂ e/year
Extended	10%	8%	136.562 GWh/year	25,674 t CO ₂ e/year

In the prudent scenario, AI applications are assumed to affect 1% of industrial electricity consumption and to reduce energy use in the targeted activities by 3%. This yields savings of 5.121 GWh and approximately 963 t CO₂e in avoided emissions per year. The intermediate and extended scenarios simultaneously assume a wider scope of application and a larger reduction in energy use, yielding savings of 42.676 GWh and 136.562 GWh, respectively. The values are rounded and conditional on the scenario assumptions; they do not represent savings already achieved by Romanian industry.

The aggregate data allow component E to be quantified but do not provide the information required to estimate components D, S, and R. The consumption of computing services depends on the architecture of each application and the location of processing, while changes in production and the rebound effect must be observed after implementation. For this reason, components D, S, and R are not assumed to equal zero, and the complete net climate balance cannot be calculated from the available data.

For each scenario, the condition required for a net climate benefit is:

$$D + S + R < E_s$$

The maximum thresholds for the sum $D + S + R$ are 963 t CO₂e/year in the prudent scenario, 8,023 t CO₂e/year in the intermediate scenario, and 25,674 t CO₂e/year in the extended scenario. If emissions from digital infrastructure, effects on the scale of production, and demand rebound together remain below the scenario threshold, $\Delta\text{GHG}(\text{AI})$ is negative and the application produces a net climate benefit. If the sum equals E_s , the balance is neutral; if it exceeds E_s , the reduction in industrial electricity consumption does not offset the additional emissions.

An enterprise can replace sector-level consumption with its own baseline consumption and calculate E from the savings measured after automation. For an investment decision, the climate assessment must be complemented by a separate economic analysis of the solution's cost, monetary savings, payback period, and project risks; a favorable climate balance does not automatically demonstrate financial viability.

4. Conclusions

This article sought to construct a framework for assessing the net climate impact associated with the use of artificial intelligence. The proposed framework compares emissions avoided through efficiency gains with emissions from digital infrastructure, changes arising from the expansion or restructuring of production, and demand rebound effects. This distinction shows that reducing energy use per unit of output is not sufficient to demonstrate a reduction in total emissions.

Applying the framework to the data available for Romania allows only partial operationalization: quantifying component E and establishing a maximum threshold for the sum of components D, S, and R. Depending on the share of industrial electricity consumption affected by

AI applications and the assumed reduction in energy use, the scenarios indicate annual electricity savings ranging from 5.121 GWh to 136.562 GWh. Using the average emission intensity of electricity generation in Romania for 2024 yields estimated avoided emissions ranging from approximately 963 to 25,674 t CO₂e per year. These results are conditional on the scenario assumptions and do not represent savings already achieved in Romania's industrial sector.

The aggregate data do not permit a complete calculation of the change in total emissions because neither the emissions from digital infrastructure nor the changes in production and demand caused by AI implementation are known. The results therefore represent assessment thresholds: AI use produces a net climate benefit only if the sum $D + S + R$ is lower than the emissions avoided through efficiency gains, represented by component E .

The framework can be used by enterprises to assess the climate impact of automation projects, provided that sector-level data are replaced with information measured at the firm level. For an investment decision, the climate balance must be complemented by an economic analysis of implementation costs, financial savings, the payback period, and project risks.

Future research can apply the framework in full to an enterprise in Romania, using measured consumption before and after automation, the use of computing infrastructure, and changes in production volume.

5. References

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