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ENERGY INFRASTRUCTURE AND AI-DRIVEN GROWTH IN THE EUROPEAN ECONOMY

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Abstract: *The widespread adoption of Artificial Intelligence (AI) is reshaping economic growth trajectories across the European Union. However, AI is not only a digital phenomenon, but it is also an energy-intensive one, which relies on physical infrastructure that is subject to policy, investment, and capacity constraints. This paper examines whether energy infrastructure is becoming a strategic bottleneck for AI-driven growth in the EU. It extends the endogenous growth model to incorporate energy as a separable input to AI production, developing three analytical scenarios of increasing specificity. The third and most realistic scenario demonstrates that when energy capital is insufficiently expanded relative to AI adoption, growth slows and a crowding-out effect emerges, compressing energy availability for households, industry, and other sectors. The theoretical findings are supported by an illustrative calibration, which confirms that the bottleneck and crowding-out dynamics identified in the model are consistent with observable trends in EU energy investment and data centre demand. The paper contributes a conceptual framework linking AI expansion, energy supply, and energy constraints. It also suggests directions for future empirical research on infrastructure constraints and AI-led growth in Europe.*

Keywords: *Artificial Intelligence, Energy Infrastructure, Economic Growth, Energy-Intensive Technologies, Data Centres, Endogenous Growth*

1 Introduction

Artificial Intelligence has become a central point of economic and policymaking agendas, driven by its importance and expected impact on increased productivity, new competitive advantages, and structural economic transformation, at both the microeconomic and macroeconomic levels, from individual firms' productivity to countries' economic growth. Isayev (2025) argues that AI is increasingly treated as a strategic pillar for building knowledge-based economies. Across the European Union (EU), firms increasingly integrate AI into their processes, such as production, logistics, finance, and management systems, while policymakers consider AI an important pillar of economic development.

However, it is important to emphasize that AI is not only a digital phenomenon. It is also an energy-intensive activity that relies on physical infrastructure, including data centres, electricity grid networks, and cooling facilities. AI training and processing take place in large-scale data centres. Based on ICIS (2025) projections, at the EU level, the power demand for data centres is expected to increase from 96TWh in 2024 to 168TWh by 2030, and further to 236TWh by 2035. This demand growth implies that data centres' power consumption will increase from 3.1% of total EU electricity consumption currently to 5.7% by 2035. Therefore, as AI systems and investments in AI facilities expand, the energy sector and particularly the electricity system, become a core production input with important implications. In the meantime, European electricity systems face various constraints. Grid capacity limitations and the need for new expansions, regulatory delays, and price sensitivity affect the ability to respond to the rapidly increasing energy demand from AI. Additionally, the latest geopolitical developments, such as armed conflicts and trade wars, make the energy system in Europe even more fragile and increase the energy risk for Artificial Intelligence.

The emerging evidence in Europe suggests that the infrastructure constraints are already relevant and important to be considered. In countries like Germany, the Netherlands, and France, the top 3 AI data centre markets in the EU, electricity demand for data centres is increasing significantly and is expected to continue to rise alongside AI deployment, by a factor of 2 times, 1.5 times, and 2.5 times, respectively, based on ICIS (2025) estimates. At the same time, grid connection delays for new data centre facilities can take over several years. All this implies that infrastructure capacities, which are not expanding at the same pace as technological developments, may create a hold-up for AI-driven growth and economic benefits.

This observation raises a central question: Is energy infrastructure becoming a bottleneck for AI development and AI-driven growth in the European Union? This paper argues that it may become. It examines how the pace of AI adoption could be constrained by energy availability and infrastructure capacity rather than technological capabilities alone, and explores the crowding-out mechanism through which rising AI energy demand may compete with households, industry, and broader development objectives within the EU.

Yet the role of energy infrastructure as a potential constraint on AI-led growth remains underexplored, as existing models do not explicitly incorporate energy as a limiting input to AI production. This paper addresses that gap by asking whether energy infrastructure is becoming a strategic bottleneck for AI-driven growth in the EU. It extends the endogenous growth model to incorporate energy as a separable and constraining input to AI production, developing three analytical scenarios of increasing specificity. The objective is to establish a conceptual framework linking AI expansion, energy supply, and macroeconomic growth dynamics, and to identify the conditions under which energy changes from an enabler to a limitation. The structure of this paper is as follows: Section 2 reviews the literature on AI, energy, and growth. Section 3 develops a theoretical framework extending the endogenous growth model by adding energy. Section 4 provides a conceptual analysis of energy as a bottleneck for AI development and AI-led growth. Sections 5 and 6, respectively, provide discussions and conclusions.

2 Literature Review on AI, Energy, and Growth

Investigating the relationship between Artificial Intelligence, energy infrastructure, and economic growth requires an intersectional examination. Scholars have studied AI as a driver of productivity, or energy as a fundamental input in production and important for industrialization, or infrastructure as a determinant of competitiveness. However, these aspects are typically developed in isolation and not as intertwined. As a result, the role of energy infrastructure as a potential constraint on AI-led growth remains underexplored.

2.1 AI and Economic Growth

Regarding the relationship between AI and economic growth, most of the existing literature is built on the endogenous models of growth, which consider technology development as an endogenous variable, as a by-product of internal economic factors such as investments in research and development (R&D), knowledge, and human capital (Romer, 1990). At the time that Romer developed the endogenous growth model, the existing models (Solow, 1956; Swan, 1956) used technology development as exogenous and assumed that technological advancements were uncontrollable. Even though both models imply that technological change is important, only the endogenous one highlights that technological progress is an active driver of economic growth.

Meanwhile, empirically, studies show that AI impacts economic growth in different ways. A panel data study (Gonzales, 2023), covering from 1970 to 2019, on AI innovation implications on economic growth suggests that there is a positive and statistically significant impact of AI patenting on average long-run economic growth. Another research study (He, 2019), with cross-province panel data from 31 Chinese provinces (2003–2019), finds that artificial intelligence has a positive and significant impact on economic growth, as well. Its empirical results suggest that AI serves as a new tool for economic development, even when controlling for other economic variables such as investment, government expenditure, consumption, and inflation. Evidence from 28 Chinese provinces over the period 2005–2018 shows that AI has both a direct and positive effect on economic growth, and a mediating effect by mitigating economic slowdown through improving the industrial structure (Fan & Liu, 2021). Furthermore, Acemoglu (2024) argues that the impact of AI on GDP and productivity depends on the share of tasks it affects and the associated cost savings at the task level. According to the study estimates, these effects are expected to be positive but modest, with total factor productivity (TFP) increasing by no more than 0.71% over the next 10 years, and potentially less than 0.55% when considering the difficulty of tasks that are harder to automate. Based on the same methodology (Acemoglu, 2024), another study (Misch et al., 2025) finds that AI is likely to increase productivity in Europe by around 1.1% over the medium run. By comparison, productivity growth is higher than US estimates, mainly due to Europe's sectoral composition and AI assumptions; however, it is still considered modest.

In different sources, evidence suggests that the AI impact on economic growth differs from one economy to another. Gonzales (2023) suggests that the effect of AI on growth is stronger among advanced economies. An OECD study (Filippucci et al., 2024) points out that AI may not benefit all countries equally and could increase the economic gap between them. This is mainly because most AI development and investment are concentrated in a few countries, especially the United States and China. Productivity gains from AI vary across countries, where higher-income nations benefit more, which may slow down income convergence within Europe (Misch et al., 2025). Isayev (2025) highlights the importance of institutional frameworks, innovation governance, and public-private coordination for AI deployment and its economic impact.

Using quarterly data for Germany from 2012 to 2022, Athari et al. (2026) employ a nonlinear ARDL framework to study the AI effects on economic growth. The results suggest that positive shocks in labour force participation and AI investment stimulate gross domestic product (GDP) growth, whereas gross fixed capital formation (GFCF) does not have a significant positive effect. Meanwhile, negative shocks to GFCF and AI investment increase GDP, demonstrating an asymmetric effect. In other top AI European markets, such as France, governmental projections (French Artificial Intelligence Commission, 2024) predict that in 10 years AI could increase GDP from €250 to €420 billion, equivalent to the added value of the total industry. Similarly, in the Netherlands, Implement Consulting Group (2024) estimates that generative AI may contribute up to 1.5% annually to productivity growth in the Netherlands, with implications for surpassing current long-term GDP growth projections as early as 2028. However, these projections do not establish a causal relationship between AI and GDP growth.

2.2 AI and Energy Infrastructure

The expansion of AI in the last decade, particularly in recent years, with the massive deployment and adoption of generative AI, is transforming the world into a digital one. However, AI remains dependent on physical means.

According to the International Energy Agency (IEA, 2025), the AI lifecycle has three main energy-intensive phases: (i) hardware manufacturing, (ii) model training, and (iii) model use. Energy demand varies across these phases. The first phase is indeed energy-intensive, especially the production of semiconductors and chips; however, it accounts for a lower energy consumption compared to the operative phases. During the second phase, the AI model training relies on massive GPU clusters, making it highly energy-intensive. In the third phase, energy demand depends on different factors such as model type, query complexity, and output type. Regarding this last phase, Electric Power Research Institute (EPRI, 2024) suggests that AI models are much more energy intensive than the data retrieval, streaming, and communication applications that were previously driving data centre growth. For instance, one ChatGPT query uses about 2.9 watt-hours, which is around ten times more electricity than a normal Google search, which only uses about 0.3 watt-hours. Also, new features, such as image generation, require even more computation, with no established efficiency benchmark yet.

In order for the AI phases to happen, large-scale facilities of AI data centres are needed. AI data centres are becoming significant electricity consumers. Based on the calculations of EPRI (2024), generally, in data centres, most of the electricity is used by IT hardware, making up around 40–50% of the total demand. Cooling systems come next, using roughly 30–40% of the total, depending on the type of cooling and the density of the servers. Additionally, the remaining 10–30% is distributed among other supporting components like the lighting, office activities, monitoring, and security system. To meet all these energy needs, globally, data centres consume approximately 1.5% of total electricity use, according to the IEA (2025). Meanwhile, EU data centres consume around 2% of the total electricity used, while it varies across countries, where, for example, in Ireland, it goes up to 20% (IEA, 2025). Moreover, IEA predicts that in the next five years, this consumption will double, with AI identified as the main factor that will drive this increase.

Beyond electricity demand, the grid network presents another significant challenge for AI deployment. Many regional grid systems may struggle to accommodate the energy. For example, although the EU has one of the most developed electricity networks, it is facing several new challenges, including limited grid capacity to handle increasing connection requests from both demand (such as electricity needs from data centres) and supply sides (increase of renewable energy supply) (European Commission, 2026). Also, the average waiting time for grid connection for the new data centres in Europe could be up to 10 years (German Data Centre Association, 2026), as further explained in section 4. Another concern is that constructing new grid lines in developed economies often takes somewhere between four and eight years to be completed (IEA, 2025). This suggests that energy infrastructure constraints merit closer analytical attention, as examined in Sections 3 and 4, particularly in the absence of new investments, infrastructure expansion, or reductions in the permitting delays mentioned above.

Considering energy infrastructure as a special form of capital has examples in the infrastructure economics literature. Aschauer (1989) demonstrates that public infrastructure investment determines productivity growth, arguing that core infrastructure, including energy and utility networks, functions as a productive input rather than just a background condition for economic activity. Also, research from Calderón and Servén (2004) confirms that the quantity and quality of infrastructure have significant positive effects on long-run growth, while deficiencies in infrastructure limit economic performance. These create a theoretical basis for seeing energy capital as an input in the growth model in the following section.

3 Theoretical Framework

Based on the existing theoretical literature and its assumptions on technological progress as a by-product of internal economic factors, this paper develops an endogenous growth model.

3.1 Endogenous Growth Model

The following specifications establish the baseline endogenous growth model.

Production equation

$Y(t) = K(t)^{\alpha} [A(t) \cdot L_{Y}(t)]^{1-\alpha}, 0 < \alpha < 1,$

Where $Y(t)$ is the total output (or total gross domestic product), $K(t)$ is physical capital (machines), $L_{Y}(t)$ is the amount of labour used in production, $A(t)$ is the stock of innovative ideas (technology), α is the elasticity of inputs, and t is time.

Labour allocation

$L = L_Y + L_A,$

Where labour L splits into L_Y as production workers and L_A as researchers.

Capital accumulation

$\dot{K}(t) = s_K Y(t) - \delta_K K(t)$

Where s_K is the savings rate, and δ_K is the depreciation rate, implying that capital *(K)* grows when we invest a part of output *(Y)*

Innovative ideas production

$\dot{A}(t) = \delta_A A(t) L_A(t)$

$g_A = \dot{A} / A = \delta_A L_A$ (growth rate of technology)

These equations imply that ideas are created based on existing ideas A and from the researcher's work L_A, highlighting that (i) knowledge builds on knowledge and (ii) technology growth is self-reinforcing, as a permanent growth without diminishing returns. It is important to mention that technology serves as a multiplier of labour.

3.2 Extension of Endogenous Growth Model: Technology Replacement with AI

As a first extension of the baseline model, technology is replaced with AI as the core driver of productivity and growth. The structure of the production equation remains the same:

$Y(t) = K(t)^{\alpha} [A^{*}(t) \cdot L_{Y}(t)]^{1-\alpha},$

But here $A^{*}(t)$ = AI capability stock, which indicates that workers are more productive because of AI tools.

AI production

$\dot{A}^{*}(t) = \delta_A A^{*}(t) L_{A*}(t)$

$g_{A*} = \dot{A}^{*} / A^{*} = \delta_{A*} L_{A*}$ (growth rate of AI)

From the AI production equation, it follows that AI improves faster when more researchers are focused and are working on the existing AI, implying that AI helps create better AI, thus creating a feedback loop. This extended model not only highlights that the existing AI creates better AI, but it may also indicate that AI assists the researcher or even might replace them. The question of AI replacing labour in the growth model is beyond the scope of this paper.

3.3 Extension of the Endogenous Growth Model: Energy as an Endogenous Factor

Another extension of the model is to introduce energy as an endogenous factor. Before doing so, it is necessary to assess whether energy can indeed be treated as endogenous. Energy infrastructure, such as power plants, electricity grids, renewable systems, etc., can be treated as endogenous because it is generated through internal economic processes, including investment and innovation. However, energy is also subject to physical constraints. Given the nature of energy, this theoretical analysis considers three alternative scenarios for incorporating it into the growth model: (i) energy embedded in technological advancement (AI), (ii) energy as a component of capital, and (iii) energy as a direct input into AI production, considering AI as energy capital-intensive.

3.3.1 First scenario: Energy embedded in AI

In this scenario, energy is not a factor that directly affects production, but it enables AI development and processing through computational capacity. Energy here is required to train models and operate data centres. More energy leads to greater computational capacity, which is also expected to accelerate AI progress. In this context, energy can be understood as the "fuel" for intelligence creation.

AI production

$\dot{A}^{*}(t) = \delta_{A*} A^{*}(t)\, L_{A*}(t)\, E(t)^{\theta}$,

$g_{A*} = \dot{A}^{*} / A^{*} = \delta_{A*}\; L_{A*} E^{\theta}$ (growth rate of AI when energy is embedded)

Where $E(t)$ is the stock of energy infrastructure that enables AI development by providing the necessary computational capacity, *and* θ is the elasticity of AI production with respect to energy.

Production model

$Y(t) = K(t)^{\alpha}\; [A^{*}(t) \cdot L_{Y}(t)]^{1-\alpha}$

The structure of the production model remains unchanged, as energy in this model does not directly produce goods but influences growth by enabling or constraining AI development. Energy functions as an innovation input rather than a production factor, affecting growth indirectly and through AI production only.

This scenario is relevant because it captures the energy demand for AI training while keeping the model simple. However, it does not account for energy use in factories, transportation, or general production. It is particularly applicable for analyzing AI-driven growth in the short to medium term.

3.3.2 Second scenario: Energy as a component of capital

In this scenario, energy infrastructure is incorporated as part of the physical capital stock:

$K = K_P + K_E$

Where K_P is the traditional capital, such as machinery and factories, etc., and K_E is the energy capital, including, for instance, power plants, electricity grids, and other related infrastructure.

Capital accumulation

$\dot{K}(t) = s_K Y(t) - \delta_K K(t)$

In the capital accumulation equation, investments automatically include both machinery and energy infrastructure, such as power plants and electricity grids. This means that energy is treated simply as another type of capital, included in the overall stock of capital rather than modeled separately, so its role in production is captured indirectly through general investment.

Production model

$Y(t) = K(t)^{\alpha}\; [A(t) \cdot L_{Y}(t)]^{1-\alpha}$

In this scenario, the structure of the production model remains unchanged as well, as energy capital is "hidden" within total capital, thus energy capital impacts growth similarly to traditional capital. Regarding its relevance, this scenario fails to capture specific issues such as energy bottlenecks and constraints.

3.3.3 Third scenario: Energy as a direct input to AI

This scenario provides a more realistic model, assuming that energy infrastructure is part of the capital and that AI depends on energy-intensive capital.

Capital stock
$K = K_P + K_E$
Capital accumulation
$\dot{K}_{E(t)} = \psi\, s_K\, Y(t) - \delta_{KE}\, K_E(t)$
$\dot{K}_{P(t)} = (1-\psi)\, s_K\, Y(t) - \delta_{KP}\, K_P(t)$
Where ψ is the share of investment going to energy, and $1 - \psi$ is the share of investment allocated to traditional capital. This setup reflects a trade-off in how the economy allocates resources between general production capacity and the expansion of energy infrastructure, and highlights that in an economy, energy investments are subject to scarcity and budget allocation.
AI production
$\dot{A}^*(t) = \delta_A\, A(t)\, L_A(t)\, K_E(t)^{\theta}$
$g_{A*} = \dot{A}^* / A^* = \delta_{A*}\ L_{A*}\, K_E^{\ \theta}$ (growth rate of AI)
Where K_E represents energy capital, as previously mentioned.
These equations indicate that energy can act as an enabler, but it can also become a bottleneck if limited, and consequently constrain AI progress and production growth.
Production equation
$Y(t) = K(t)^{\alpha}\ [A(t) \cdot L_{Y(}t)]^{1-\alpha}$

In this scenario, the structure of the production equation remains unchanged while introducing a new mechanism without breaking the model, demonstrating that the endogenous growth model is still highly relevant. However, the sources of production growth are further explored, as energy is explicitly included as part of capital and also serves as a specific production input in AI production.

Additionally, this scenario is more realistic, as it highlights the importance of energy for AI and distinguishes energy capital from traditional capital. In this way, it helps capture the need to invest both in production capital, such as data centre facilities, and in energy capital, such as the expansion of electricity grids, for instance.

Key results

1. If $\psi \approx 0$, investments in K_E remain limited, which results in a slowdown of the rate of AI growth.
2. If ψ is high, even small increases in energy capital can generate large increases in AI growth, potentially leading to faster growth in production.
3. Unlike in the baseline model, where ideas grow without physical constraints, AI in this framework is no longer “free,” as its growth depends on the availability and expansion of energy infrastructure.

3.3.4 Comparative analysis of scenarios

Table 1 summarises the three scenarios, comparing how energy is incorporated into the model, its impact on growth, and the relevance of each scenario.

Table 1. *Energy incorporation in the endogenous growth model, based on three scenarios*

Scenario	*Energy integration*	*Energy impact on growth*	*Scenario relevance*
1st	Part of the AI, not of the production function	Indirect effect: energy increases computational capacity → faster AI growth → higher productivity	Useful to explain AI-driven growth specifically in the short run, but ignores energy more broadly
2nd	Part of the total capital	Indirect and unclear effect: energy affects production through capital accumulation	Useful when energy is not a constraint
3rd	Part of both capital and an input in AI production through energy capital	Direct and indirect effects: energy supports AI development and thus drives productivity or limits growth	Useful for studying AI–energy interactions and long-run growth, and it captures energy both as enabler and bottleneck.

3.3.5 Illustrative Model Calibration

To test if the third scenario reflects real EU conditions, this section provides estimated values for the key parameters using some available data. The goal is not to forecast, but to show that the theoretical relationships are not abstract.

Calibrating ψ - energy investment share

EU grid investment currently stands at roughly €65 billion, against total gross fixed capital formation of €3.8 trillion (21.2% of EU GDP of €17.9 trillion), giving $\psi_0 \approx 0.017$ (IEA, 2025; Eurostat, 2025). With AI-driven data centre energy demand projected to grow by 150% by 2035 (ICIS, 2025), the required investment share rises to an estimated 0.030–0.050. Three scenarios are used, as in Table 2, below:

Table 2. *Energy Investment Scenarios Used in the Calibration*

Scenario	ψ	Interpretation
Low *(status quo)*	0.017	Current EU grid investment, no expansion
Medium *(partial adjustment)*	0.030	Energy investment 2x (EC Grid Action Plan)
High *(full adjustment)*	0.050	Energy investment 3x, sufficient for AI demand growth

Source: Authors' own elaboration based on IEA (2025), Eurostat (2025), and ICIS (2025)

Calibrating θ — energy elasticity of AI output

AI electricity consumption is growing at approximately 30% per year (IEA, 2025), while AI economic output for Europe grows at an estimated 9–18% per year (Misch et al., 2025). Dividing output growth by energy input growth gives:

θ = output growth/energy input growth ≈ 0.09/0.30=0.30 or *0.18/0.30=0.60*

A central value of $\theta = 0.40$ is used, meaning that a 10% increase in energy capital gives roughly a 4% increase in AI output. This is a conservative estimate reflecting that energy is one of several inputs to AI production.

Calibrating g_A and summary results

Applying these values to the growth equation $g_A = \delta_A \cdot L_A \cdot K_E^{\theta}$ from Section 3.3.3, and scaling K_E in proportion to ψ (baseline $K_E = 1$ at $\psi = 0.017$), Table 3 summarises the results across the three scenarios.

Table 3. *Calibration results across energy investment scenarios*

Parameter / Outcome	***Low ψ** (0.017)*	**Medium ψ** *(0.030)*	**High ψ** *(0.050)*
Energy capital index (KE)	1.00	1.76	2.94
AI growth index (g_A, $\theta = 0.40$)	1.00	1.26	1.52
Cumulative TFP gain (10 years)	~1.1%	~1.4%	~1.7%
Crowding-out pressure	High	Moderate	Low
Policy implication	Bottleneck	Partial relief	Relief

Source: Authors' own calculations based on IEA (2025), Eurostat (2025), Misch et al. (2025), Ember (2025), and ICIS (2025)

Three findings are noticeable:

1. First, doubling energy investment raises cumulative TFP gains from ~1.1% to ~1.4%, and tripling it to ~1.7% over ten years, a meaningful but not transformative difference, consistent with Misch et al. (2025) and with Acemoglu's (2024) view that AI's macroeconomic impact will be modest in the medium term.
2. Second, even under the high scenario, energy infrastructure is necessary but not sufficient for AI-led growth.
3. Third, and most critically, under current investment levels, AI data centre demand is on track to absorb all incremental EU electricity supply growth by 2030, leaving nothing for households or industry. This is the crowding-out dynamic the model predicts, now visible in real data.

These figures are illustrative, not econometric. The θ parameter in particular cannot yet be precisely estimated, as systematic data on AI capital spending and AI output at the EU country level does not yet exist. Estimating θ from EU panel data should be a priority for future empirical work.

3.4 Limitations of the theoretical model

This paper has a simplified theoretical framework and relies on assumptions that should be acknowledged:

- First, it assumes that energy supply and infrastructure adjust slowly relative to the pace of AI expansion. This assumption is motivated by the nature of energy infrastructure investment, which is highly capital-intensive, subject to administrative and permitting delays, and often requires many years to be completed. In this context, treating energy as fixed in the short and medium run provides a realistic assumption for analyzing potential bottlenecks related to rapid AI deployment.
- Second, the model does not explicitly include energy efficiency improvements. This simplification is consistent with the purpose of the framework, which is to isolate the role of energy availability as a constraint on AI-driven growth. Also, in endogenous growth models, technological progress is typically treated as the main driver of productivity growth itself, rather than modeling separate efficiency dynamics for each production input.
- Currently, the model does not empirically estimate the magnitude of the proposed bottleneck effects. So, the framework should be interpreted as an analytical tool for understanding possible mechanisms linking AI expansion, energy infrastructure, and economic growth, rather than as a predictive quantitative model.

4 Conceptual Analysis

The theoretical framework developed above, in particular the third scenario, explains the role of energy as a necessary input in AI production. From this, the following conceptual framework is built to further interpret these relationships in economic terms with more practical examples and evidence.

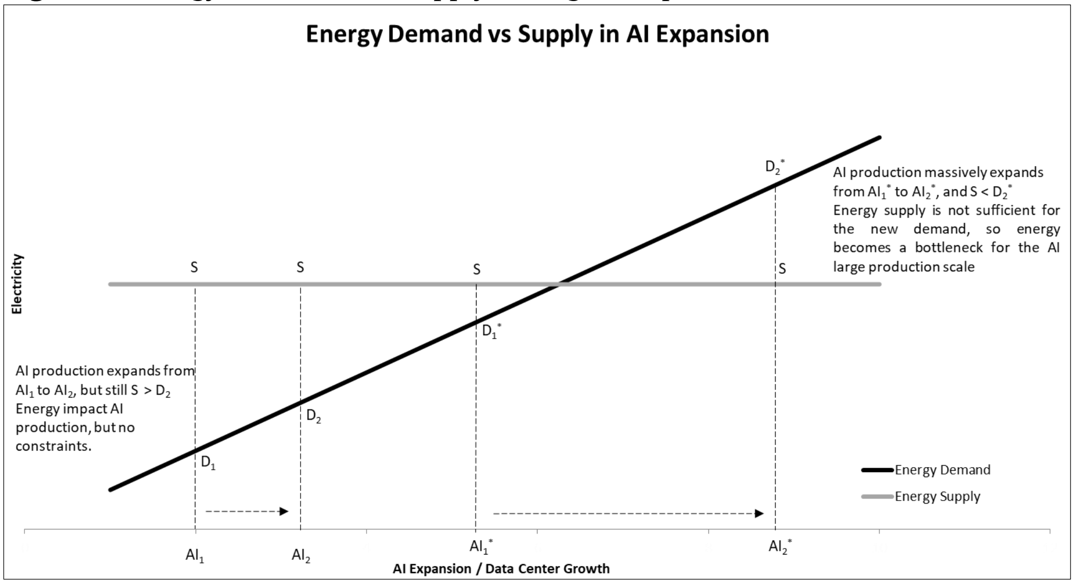
4.1 AI growth: Energy Demand and Supply Impact

In this section, for analytical purposes, it is assumed that energy supply, including electricity grids and production capacity, remains fixed over time, without significant expansion or any change.

Even in the early stages of artificial intelligence development, energy is a very important input factor, and as AI systems expand (from AI_1 to AI_2), the existing stock of energy is still able to meet the increasing demand (from D_1 to D_2). However, if in the future the energy supply continues to remain constant (S=constant), while AI continues to advance and expand in scale, new technologies or applications, the energy demand is expected to increase even more (from D_1^* to D_2^*), leading to a situation where demand exceeds available energy stock ($S < D_2^*$).

This situation would result in a supply deficiency in the energy market, creating constraints that limit the ability of economies to develop more AI and to fully benefit from AI development, and eventually turning energy into a critical bottleneck for growth. This dynamic suggests that without parallel investments in energy infrastructure, the expansion of AI may be restricted by physical energy limitations, as it is illustrated in Figure 1, which shows the gap between fixed supply and increasing demand over time.

Figure 1. *Energy Demand and Supply during AI Expansion.*

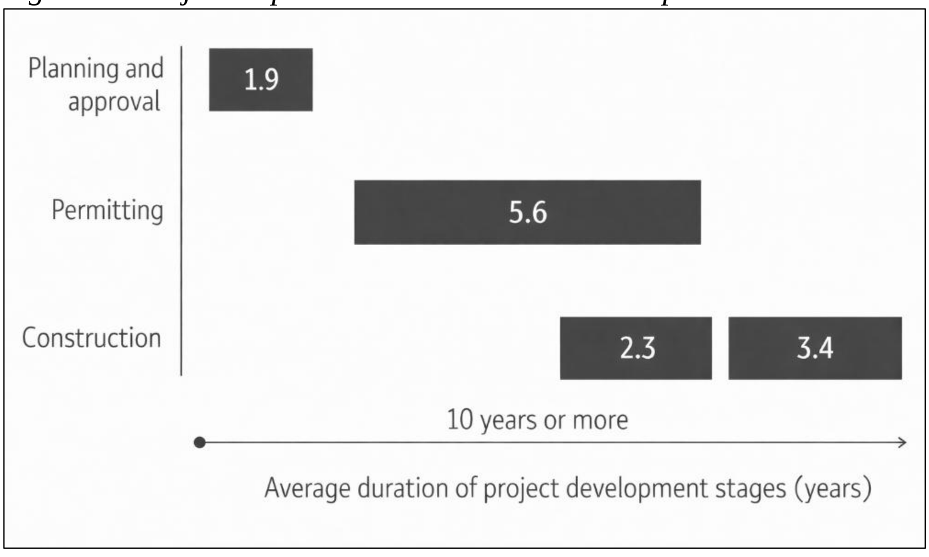


Source: Authors' own elaboration

4.2 Energy capital constraints

Figure 2

Average Grid Project Implementation Time in the European Union

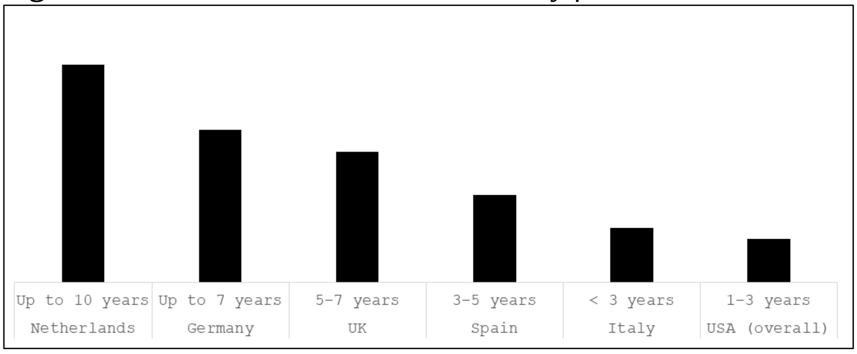


Source: EPRS, 2025

Based on the theoretical framework built above and the assumption that energy can be assumed as capital, it can be argued that capital cannot be created quickly, and it requires time to accumulate. Thus, energy capital faces limits in how fast it can expand. To bring this into practical terms with an example, what becomes most evident is the long time required for the new grid's implementation. Infrastructure projects typically take more than 10 years to be completed, with a very large share of this period being consumed by administrative permitting processes alone (European Parliamentary Research Service [EPRS], 2025), as shown in Figure 2, which presents the average grid project implementation timeline in the EU.

Apart from the time-consuming implementation of new grid projects, grid connection waiting times for data centres also represent a major bottleneck for AI competitiveness in terms of energy access. As shown in Figure 3, in leading EU data centre markets such as Germany and the Netherlands, grid connection waiting times can reach 7–10 years

Figure 3. *Estimated Grid Connection Delay for Data Centres*



Source: IEA, 2025

Additionally, capital has to be allocated between different uses, mainly between traditional capital (like infrastructure and production) and energy capital (such as grids and energy systems). This investment trade-off, introduced in Section 3.3.3, has direct practical implications.

4.3 Crowding out effect

Energy constraints turn energy into a key bottleneck, limiting sectors that use a lot of energy, such as AI, industry, transport, households, and other sectors. When different users compete for the same energy supply, which is assumed to be fixed or not experiencing significant changes over time, prices tend to increase. This situation can be described as a crowding-out effect, where the expansion of one sector reduces the energy available for others, expressed in a simple way as:

$$E_{total} = E_{households} + E_{transport} + E_{industry} + E_{AI} + E_{others}$$

When total energy supply remains fixed, an increase in energy use by AI → reduces the energy available for other sectors → creates crowding out → leads to higher prices and constrained growth.

The competition becomes concrete when considering that a single AI-focused data centre consumes as much electricity as 100,000 households, while the largest facilities currently under construction are projected to consume twenty times that amount (IEA, 2025). When total energy supply remains constrained, the expansion of even a small number of such facilities can affect the energy available for residential, industrial, and other productive uses, which is precisely what the crowding-out model describes.

In this way, energy can become a constraining factor as a result of AI expansion itself, as its high energy demand may start to limit the growth it is expected to generate. At the same time, other sectors cannot expand as needed. Overall, this conceptual analysis shows that if energy supply does not grow, it limits both AI and broader economic growth.

5 Discussions and Policy Implications

The theoretical framework developed in section 3, based on the endogenous growth model (Romer, 1990) and the infrastructure literature (Aschauer, 1989; Calderón & Servén, 2004), suggested that energy infrastructure is not merely a passive background condition for AI-driven growth. The following discussion interprets this in economic and policy terms, referring to the European Union.

- Grid connection to data centres taking up to 7 - 10 years in top EU data centre markets, such as Germany and the Netherlands (German Data Center Association, 2026; IEA, 2025), means that infrastructure decisions made today will determine AI competitiveness in the upcoming 10 years.
- Grid construction timelines of ten or more years (EPRS, 2025) suggest that the acceleration of permitting processes is as critical as the investment itself.
- The crowding-out effect becomes tangible when considered at the scale of actual infrastructure as analysed in Sections 3.3.3 and 4.3. For policymakers, the scale of AI energy consumption creates difficult trade-offs: prioritising data centres connectivity may accelerate AI-driven growth, but at the cost of household energy affordability and industrial competitiveness. This highlights that expanding energy capital investment is not optional if both AI development and broader social welfare are policy objectives.
- The investment share distributed to energy capital (ψ, as defined in Section 3.3.3) should be treated as a strategic policy indicator rather than a market result. So, policymakers need to make decisions on how much capital to invest in energy.
- The crowding-out risk underscores the need to explore mechanisms that offset data centre energy consumption. For example, Google has integrated waste heat from its Frankfurt data centre into the regional EVO district heating network, supplying an estimated 2,000 households.

6 Conclusions

The main finding is direct. When energy infrastructure does not expand with AI deployment, AI and broader economic growth slow, a result that follows directly from the third scenario of the extended endogenous growth model (Section 3.3.3), where insufficient energy capital investment constrains AI production and reduces the overall growth rate. When energy supply is constrained, rising AI energy demand competes with households, industries, and other sectors' needs, creating trade-offs (as illustrated through the crowding-out framework in Section 4). This suggests that grid investment and permitting reforms are not secondary energy policy issues but important components of any serious AI strategy in the EU.

The paper has a few limitations. It is theoretical, and its conclusions are conditional on the assumption that energy supply expands slowly relative to AI demand, an assumption consistent with current EU grid data (IEA, 2025; EPRS, 2025) but one that may not hold under accelerated infrastructure investment scenarios. It also does not consider how the energy transition, improved energy efficiency, or increased software and hardware efficiency may ease the bottleneck. The calibration exercise provides additional support for the theoretical framework by illustrating how energy infrastructure constraints may translate into differences in AI-driven growth, although it is not intended to provide precise empirical estimates. Future research should focus on empirically testing the bottleneck hypothesis and empirically calibrating the energy capital framework to offer guidance to policymakers.

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Annex - Calculations for Model's Calibration

Baseline values

$\psi_0 = 0.017$ — current EU energy investment share (IEA, 2025; Eurostat, 2025)

$\theta = 0.40$ — central estimate of energy elasticity of AI output

$K_E = 1.00$ at baseline (*set at* $\psi_0 = 0.017$)

Energy capital index

$K_E = \psi / \psi_0$

Low: 0.017 / 0.017 = 1.00

Medium: 0.030 / 0.017 = 1.76

High: 0.050 / 0.017 = 2.94

AI growth index

($g_A = K_E$^0.40)

Low: 1.00^0.40 = 1.00

Medium: 1.76^0.40 = 1.26

High: 2.94^0.40 = 1.52

Cumulative TFP gain ($TFP_s = TFP^{base} \times g_a$)

Baseline: 1.10% cumulative TFP gain for Europe (Misch et al., 2025)

Low ($g_a = 1.00$)*:* 1.10% × 1.00 = 1.10% ≈ 1.1%

Medium ($g_a = 1.26$)*:* 1.10% × 1.26 = 1.39% ≈ 1.4%

High ($g_a = 1.52$)*:* 1.10% × 1.52 = 1.67% ≈ 1.7%

Table A1. *Summary of Formulas Used in the Calibration*

Indicators	Formulas
Energy investment share	ψ_0 = grid investment / GFCF
Energy capital index	$K_E = \psi / \psi_0$
AI growth index	$g_a = K_E^{\theta}$
TFP gain per scenario	$TFP_s = TFP^{base} \times g_a$
θ bounds	output growth rate/energy input growth rate