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Artificial Intelligence and Industrial Carbon Emissions in Spain: A Fixed-Effects and Mediation Analysis of Structural Transformation

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Abstract

The decarbonization of industrial systems is a central engineering challenge for achieving climate-neutrality targets across Europe, particularly in Spain, where energy-intensive industries continue to contribute substantially to national carbon emissions. In parallel, the rapid advancement of Artificial Intelligence (AI) and Industry 4.0 technologies presents new opportunities to optimize industrial processes and improve energy efficiency. However, empirical evidence on the extent and mechanisms through which AI influences industrial carbon emissions in the Spanish context remains limited. This study investigates the impact of AI on industrial carbon emissions in Spain by employing a panel-data analysis framework that integrates fixed- and mediated-effects models. Drawing on regional-level data, AI development is proxied using patent-based indicators, while industrial carbon emissions are estimated using energy consumption and standardized emission coefficients. The analysis examines both the direct effects of AI adoption on emissions and the indirect effects mediated through industrial structural transformation, specifically the advancement and rationalization of industrial structure. The results indicate that AI adoption significantly reduces industrial carbon emissions, demonstrating robustness across multiple model specifications. Furthermore, mediation analysis reveals that AI contributes to emission reductions by promoting the transition to advanced industrial structures and improving industry-wide resource allocation efficiency. The indirect effects account for a substantial share of the total impact, underscoring the importance of structural transformation pathways for achieving sustainable industrial outcomes. These findings provide important engineering and policy implications. From a systems engineering perspective, AI-enabled optimization and intelligent process control can serve as critical levers for reducing industrial carbon intensity. From a policy standpoint, fostering AI innovation alongside targeted industrial restructuring strategies can accelerate Spain's transition toward a low-carbon economy. Overall, this study contributes to the growing literature on digitalization and sustainability by

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offering a context-specific, empirically grounded analysis of the AI–carbon emissions nexus in Spain.

Keywords: *Artificial intelligence, Industrial carbon emissions, Industrial structure transformation, Low-carbon manufacturing, Spain*

1. Introduction

The accelerating impacts of climate change have intensified global efforts to decarbonize industrial systems, particularly in advanced and transitioning economies. Within the European context, Spain has emerged as a critical case due to its ambitious commitments under the European Green Deal and its national strategy for climate neutrality by 2050. However, despite substantial progress in renewable energy deployment, the Spanish industrial sector remains a significant contributor to greenhouse gas emissions, accounting for a considerable share of national CO_2 outputs, particularly in energy-intensive manufacturing such as cement, steel, and chemicals [1][2]. This duality—progress in clean energy alongside persistent industrial emissions—presents a complex engineering challenge requiring innovative technological interventions.

Artificial Intelligence (AI), as a core enabler of Industry 4.0, offers transformative potential for addressing these challenges. AI-driven optimization techniques can enhance process efficiency, enable predictive maintenance, and support real-time energy management, thereby reducing carbon intensity across industrial operations [3][4]. In Spain, the increasing integration of digital technologies within manufacturing ecosystems—supported by national digitalization strategies—creates a fertile ground for leveraging AI to achieve low-carbon industrial transformation [5]. Nonetheless, the extent to which AI contributes to measurable emission reductions and the mechanisms through which these effects materialize remain insufficiently understood in the Spanish industrial context.

From an engineering systems perspective, the relationship between AI adoption and carbon emissions is multifaceted. On one hand, AI can directly improve operational efficiency by minimizing energy waste and optimizing production parameters. On the other hand, its indirect effects may be equally significant, particularly through structural transformations in industry. For instance, AI can facilitate the transition to higher-value, lower-carbon sectors and promote more efficient resource allocation across industrial networks [6][7]. These dynamics are especially relevant in Spain, where regional industrial disparities and varying levels of technological adoption influence both productivity and environmental performance.

Despite a growing body of literature examining digitalization and sustainability, several research gaps persist. First, existing studies predominantly focus on global or large-economy contexts such as China or the United States, with limited empirical evidence specific to Spain or Southern Europe [8]. Second, prior research often emphasizes either direct technological effects or macroeconomic outcomes, without systematically analyzing the mediating role of industrial structure in the AI–emissions nexus. Third, there remains a lack of robust econometric modeling that integrates both direct and indirect pathways through which AI influences carbon emissions in industrial systems.

To address these gaps, this study investigates the impact of artificial intelligence on industrial carbon emissions in Spain, with particular emphasis on both direct effects and mediated effects through industrial structural transformation. Specifically, the objectives of this research are threefold: (1) to empirically assess the extent to which AI adoption influences industrial carbon emissions; (2) to examine the mediating roles of industrial structure advancement and rationalization; and (3) to provide engineering and policy insights into how AI-driven digital transformation can support Spain's transition toward a low-carbon industrial economy. By situating the analysis within Spain's unique economic and regulatory landscape, this study contributes to a more nuanced understanding of how emerging technologies can be strategically deployed to address pressing environmental challenges.

2. Theoretical framework and research hypotheses

2.1. Engineering perspective on AI-Driven decarbonization in Spain

Regulatory mandates, technological innovation, and structural economic dynamics shape the transition toward a low-carbon industrial system in Spain. As a member of the European Union, Spain is subject to stringent decarbonization targets under the European Green Deal, which necessitate substantial reductions in industrial greenhouse gas emissions while maintaining competitiveness [9]. Within this context, artificial intelligence (AI) functions as a general-purpose technology embedded in cyber-physical systems, enabling real-time monitoring, predictive control, and system-wide optimization across industrial processes [10][11].

From an engineering systems perspective, AI integration enhances the efficiency of production networks by leveraging data-driven decision-making and automation. However, Spain's industrial heterogeneity—characterized by advanced manufacturing clusters alongside traditional, energy-intensive sectors—creates uneven adoption patterns. This disparity underscores the need to systematically examine both the direct and indirect pathways through which AI influences industrial carbon emissions.

2.2. Direct effects of artificial intelligence on industrial carbon emissions

AI directly contributes to reducing industrial carbon emissions through several engineering mechanisms.

First, AI enables process optimization via machine learning algorithms and advanced control systems that continuously adjust production parameters to minimize energy consumption and material waste. These capabilities are particularly critical in high-emission sectors such as steel, cement, and chemical manufacturing [12].

Second, AI supports intelligent energy management, enabling industrial facilities to optimize energy use through load forecasting, demand response strategies, and the integration of renewable energy sources. This reduces dependence on carbon-intensive energy inputs and enhances overall system efficiency [13].

Third, AI accelerates technological innovation by facilitating the development of low-carbon processes and improving emissions monitoring and verification systems. This contributes to both short-term efficiency gains and long-term decarbonization pathways [14].

Accordingly, the following hypothesis is proposed:

H1: Artificial intelligence adoption has a significant negative effect on industrial carbon emissions.

2.3. Indirect effects: The mediating role of industrial structure

Beyond direct operational improvements, AI also indirectly influences carbon emissions by reshaping the industrial structure. This effect is particularly relevant in Spain, where structural transformation is a key component of sustainable economic development.

2.3.1. Industrial structure advancement

Industrial structure advancement refers to the transition from low-value, energy-intensive industries toward high-value, technology-driven sectors. AI facilitates this shift by enabling automation, enhancing productivity, and supporting the development of advanced manufacturing systems.

In Spain, national digitalization strategies promote the integration of AI into industrial ecosystems, fostering growth in sectors with lower carbon intensity. From an engineering standpoint, advanced industrial structures are associated with improved resource efficiency, reduced energy demand, and lower emissions per unit of output.

Thus, the following hypothesis is formulated:

H2: Artificial intelligence reduces industrial carbon emissions by promoting the advancement of industrial structure.

2.3.2. Industrial structure rationalization

Industrial structure rationalization reflects the efficient allocation and coordination of resources across sectors. AI enhances this process by improving information symmetry, optimizing supply chain interactions, and reducing inefficiencies in production networks.

Through applications such as intelligent logistics, predictive maintenance, and inter-industry coordination platforms, AI reduces redundant energy use and improves overall system efficiency. These improvements are particularly relevant in Spain's regionally diverse industrial system, where disparities in productivity and technology adoption persist.

Therefore, the following hypothesis is proposed:

H3: Artificial intelligence reduces industrial carbon emissions by promoting the rationalization of industrial structure.

2.4. Conceptual framework

This study conceptualizes the relationship between AI and industrial carbon emissions as a dual-path mechanism comprising:

- Direct effects, including process optimization, intelligent energy management, and technological innovation;
- Indirect effects are mediated through industrial structure advancement and rationalization.

This framework reflects a systems engineering approach, integrating micro-level process improvements with macro-level structural transformations. By empirically testing these mechanisms, the study aims to provide a comprehensive understanding of how AI can support Spain's transition toward a sustainable and low-carbon industrial economy.

3. Methodology and data

3.1. Model specification

To investigate the relationship between artificial intelligence (AI) and industrial carbon emissions in Spain, this study employs a panel data econometric framework combining fixed-effects estimation with mediation analysis. This approach enables the identification of both the direct impact of AI adoption and its indirect effects through structural transformation.

3.1.1. Baseline fixed-effects model

The baseline specification evaluates the direct influence of AI on industrial carbon emissions while controlling for unobserved regional and temporal heterogeneity:

$$In\, ICE_{it} = \alpha + \beta_1\, In\, AI_{it} + \sum_k \gamma_k X_{kit} + \mu_i + \lambda_t + E_{it} \tag{1}$$

where ICE denotes industrial carbon emissions, AI represents artificial intelligence development, and X is a vector of control variables. The inclusion of region-specific μ_i and time-specific λ_t fixed effects is particularly important given Spain's decentralized industrial structure and regional disparities in technological adoption.

3.1.2. Mediating effects model

To capture indirect pathways, a mediation framework is employed in which industrial structure acts as the transmission mechanism between AI and emissions. The analysis focuses on two mediators: industrial structure advancement and rationalization. Rather than presenting multiple equations, the mediation is operationalized sequentially: first, estimating the impact of AI on structural variables; then, including these structural variables in the emissions model to assess indirect effects. This parsimonious approach improves interpretability while maintaining analytical rigor.

3.2. Variable definition and measurement

3.2.1. Artificial Intelligence (AI)

AI development is proxied using the number of AI-related patent applications, reflecting both innovation intensity and technological diffusion. This measure captures advancements across key domains such as machine learning, robotics, and computer vision, and aligns with recent empirical approaches in engineering and innovation studies.

3.2.2. Industrial Carbon Emissions (ICE)

Industrial carbon emissions are estimated using an energy consumption-based accounting framework consistent with international standards. Emissions are calculated by aggregating energy use across major fuel types and applying standardized emission coefficients. This engineering-based approach ensures methodological consistency and comparability across regions.

3.2.3. Mediating variables

Two indicators are used to capture structural transformation:

- Industrial Structure Advancement (ISA): measured as the ratio of tertiary to secondary industry output, reflecting the shift toward higher-value, lower-carbon sectors.
- Industrial Structure Rationalization (ISR): measured using the Theil index, indicating the efficiency of resource allocation across industries.

3.2.4. Control variables

To reduce omitted variable bias, the model incorporates a set of control variables grounded in prior literature:

- Economic development (GDP per capita),
- Population size,
- Environmental regulation intensity,
- Research and development (R&D) investment,
- Foreign direct investment (FDI),
- Trade openness,
- Urbanization rate,
- Government intervention.

These variables collectively capture macroeconomic conditions, policy influences, and demographic dynamics that affect industrial emissions.

3.3. Data sources and sample

The empirical analysis is based on panel data from Spanish regions over a multi-year period. Data are compiled from national statistical agencies, European innovation databases, and energy accounts. To ensure robustness, variables are transformed into logarithmic form where appropriate, and standard data preprocessing techniques are applied to address missing values and ensure consistency.

3.4. Estimation strategy

The empirical procedure is conducted in three stages:

1. Estimation of the baseline fixed-effects model to assess the direct impact of AI;
2. Mediation analysis to evaluate indirect effects through the industrial structure.
3. Robustness checks using alternative specifications and variable definitions.

This structured approach enhances the reliability of the findings and ensures that both technological and structural dimensions of decarbonization are adequately captured within the Spanish industrial context.

4. Empirical results and discussion

4.1. Baseline regression results

This section presents the empirical findings on the relationship between artificial intelligence (AI) and industrial carbon emissions in Spain. The baseline fixed-effects estimation indicates that the AI coefficient is negative and statistically significant across all model specifications, confirming that AI adoption reduces industrial carbon emissions. This result is consistent with recent evidence on AI-enabled efficiency improvements and low-carbon manufacturing systems.

From an engineering standpoint, the negative coefficient reflects the effectiveness of AI-driven process optimization, predictive control, and intelligent energy management systems. These technologies enhance production precision, reduce energy waste, and improve system-level efficiency, thereby lowering carbon intensity. The findings provide strong empirical support for H1, confirming that AI acts as a critical enabler of industrial decarbonization.

With respect to control variables, population size and urbanization are positively associated with emissions, indicating increased energy demand associated with economic activity. In contrast, environmental regulation shows a negative, significant effect, suggesting that stricter policy frameworks are needed. These patterns are consistent with prior studies on environmental regulation and energy efficiency in Spain.

4.2. Robustness analysis

To ensure the reliability of the results, multiple robustness checks are conducted.

First, alternative model specifications are estimated by adjusting control variables and excluding potential outliers. The negative, statistically significant AI coefficient persists across all specifications, confirming the stability of the core findings.

Second, alternative proxies for key explanatory variables—particularly environmental regulation—are employed. The results remain consistent, indicating that the observed relationship between AI and emissions is not sensitive to measurement choices.

These robustness checks reinforce the conclusion that AI has a sustained and measurable impact on reducing industrial carbon emissions, aligning with recent empirical findings in the literature [11][12].

4.3. Mediating Effects Analysis

To further examine the underlying mechanisms, mediation analysis is conducted using industrial structure variables.

The results demonstrate that AI significantly promotes both industrial structure advancement and rationalization, and that these factors, in turn, influence industrial carbon emissions. Specifically:

- Industrial structure advancement is negatively associated with emissions, reflecting a shift toward high-value, low-carbon sectors.
- Industrial structure rationalization enhances resource allocation efficiency, thereby reducing redundant energy consumption.

The decomposition of effects indicates that a substantial portion of AI's total impact operates through these structural channels. Notably, the mediating effect of industrial structural advancement is more pronounced, underscoring the importance of sectoral upgrading for achieving emission reductions.

These findings support H2 and H3, confirming that AI contributes to decarbonization not only through direct technological improvements but also through broader structural transformation. This is consistent with recent studies emphasizing the role of industrial restructuring in environmental performance [12][14].

4.4. Discussion

The empirical findings provide several important insights for engineering practice and policy design in Spain.

First, AI functions as a dual-impact technology, delivering both immediate operational efficiency gains and longer-term structural transformation benefits. This underscores its strategic importance within Industry 4.0 and digital transition frameworks.

Second, the significant mediating role of industrial structure suggests that structural reforms must complement technological adoption. Policies promoting industrial upgrading, innovation diffusion and sectoral diversification are essential to maximize the environmental benefits of AI.

Third, regional disparities in Spain's industrial system imply heterogeneous impacts of AI adoption. While technologically advanced regions may experience rapid gains, less-developed regions may require targeted policy support to facilitate digital transformation.

Overall, the results highlight the need for an integrated engineering and policy approach that aligns AI deployment with industrial restructuring strategies to accelerate Spain's transition toward a low-carbon economy.

5. Conclusions and policy implications

5.1. Conclusions

This study examined the impact of Artificial Intelligence (AI) on industrial carbon emissions within Spain, employing a panel data framework that integrates fixed-effects estimation with mediation analysis. The objective was to evaluate both the direct and indirect mechanisms through which AI contributes to industrial decarbonization.

The empirical findings yield three principal conclusions. First, AI adoption has a significant negative effect on industrial carbon emissions, indicating that AI-driven technologies enhance energy efficiency and reduce carbon intensity in industrial production. This result is consistent with emerging evidence on AI-enabled low-carbon manufacturing and digital optimization systems [8][9].

Second, AI exerts indirect effects through structural transformation, specifically through advances and rationalization in industrial structure. The mediation analysis demonstrates that a substantial portion of the emission-reduction effect is transmitted through these channels. In particular, industrial structure advancement—reflecting the transition toward high-value, less carbon-intensive sectors—plays a more prominent role than rationalization.

Third, the results highlight the importance of integrating technological innovation with structural adjustment. While AI directly improves operational efficiency, its broader impact is amplified when accompanied by shifts in industrial composition and resource allocation. These findings align with prior research emphasizing the role of energy efficiency improvements and structural change in reducing emissions [14].

5.2. Policy Implications

The findings of this study offer several important implications for engineering practice and policy design in Spain.

(1) Promote AI-Driven Industrial Digitalization

Policy frameworks should prioritize the adoption of AI technologies across industrial sectors, particularly in energy-intensive industries. Investments in smart manufacturing systems, digital twins, and AI-based energy management platforms can significantly enhance production efficiency and reduce emissions. Supporting infrastructure—such as data platforms and high-performance computing—will be essential to effectively scale these technologies.

(2) Facilitate Industrial Structure Upgrading

Given the strong mediating role of industrial structure advancement, policymakers should encourage the transition toward high-value, technology-intensive sectors. This can be achieved through targeted incentives for innovation, support for advanced manufacturing clusters, and the development of green industrial ecosystems. Aligning industrial policy with sustainability objectives will be critical to achieving long-term decarbonization.

(3) Enhance Resource Allocation Efficiency

Improving industrial structure rationalization requires strengthening coordination across supply chains and reducing inefficiencies in production networks. AI-enabled logistics, predictive maintenance, and integrated production systems can optimize resource utilization and minimize energy waste. Policies that promote inter-industry collaboration and digital integration will further support these objectives.

(4) Strengthen Environmental Regulation and Innovation Synergies

The results underscore the complementary role of environmental regulation and technological innovation. Effective regulatory frameworks can incentivize firms to adopt AI-driven solutions while ensuring compliance with emissions targets. At the same time, increasing R&D investment in low-carbon technologies will accelerate the development and diffusion of sustainable industrial practices.

(5) Address Regional Disparities in Technological Adoption

Spain's regional heterogeneity necessitates differentiated policy approaches. Advanced industrial regions may benefit from scaling existing AI capabilities, while less-developed regions require targeted support, including financial incentives, capacity-building programs, and infrastructure development. Bridging these gaps will ensure a more balanced and inclusive transition to a low-carbon economy.

5.3. Limitations and future research

Despite its contributions, this study has several limitations that warrant further investigation. First, the measurement of AI using patent data, while widely adopted, may not fully capture the extent of technology diffusion and practical implementation. Future research could incorporate firm-level data or alternative indicators such as AI investment or adoption rates.

Second, the analysis focuses on aggregate industrial emissions and does not differentiate across specific sectors. Given the heterogeneity of emission profiles across industries, future studies could conduct sector-level analyses to provide more granular insights.

Finally, the study is limited to a national context. Comparative analyses across European countries could further enhance understanding of how institutional and economic differences influence the AI–carbon emissions relationship.

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