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Research Article

Artificial Intelligence and Energy Efficiency in the EU: A Dynamic Panel Approach

Ali Rıza Solmaz,[1] **Murat Emikönel**,[1] **Özgür Bayram Soylu**,[1] **and Magdalena Radulescu**[2,3]

[1]*Department of Economics, Faculty of Political Sciences, Kocaeli University, Kocaeli 410001, Türkiye*
[2]*Department of Finance, Accounting and Economics, National University of Science and Technology, Politehnica, Bucharest, Romania*
[3]*UNEC Research Methods Application Center, Azerbaijan State University of Economics (UNEC), Baku, Azerbaijan*

Correspondence should be addressed to Magdalena Radulescu; magdalena.radulescu@upb.ro

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Energy intensity comes to the forefront in evaluating the efficiency of energy consumption in economic activities. While countries' environmental policies, production techniques, and foreign trade frameworks have an impact on energy intensity, today the impact of artificial intelligence (AI) and related factors on energy intensity has also begun to be examined. This research analyzes the influence of AI on energy intensity utilizing data from 2005 to 2022 for 27 European Union (EU) nations. An AI index was initially established via the PCA approach incorporating 15 AI-related factors. The two-stage system generalized method of moments (GMM) was employed to ascertain the impacts of the pertinent AI index, trade openness, industrial production, and governance factors on energy intensity. The results indicate that the prevalence of AI technologies, the degree of trade openness, and the level of industrial production enhance energy efficiency. Nonetheless, the regulatory quality (RQ) fails to convey a favorable impression about the assurance of energy efficiency. The findings underscore the necessity of incorporating AI into strategies aimed at enhancing energy efficiency in manufacturing processes for policymakers and stakeholders in industrial production.

Keywords: artificial intelligence; energy intensity; government effectiveness; industrial production; regulatory quality; trade openness

1. Introduction

One of the most significant environmental challenges confronting the global community pertains to emissions, which constitute the principal source of environmental hazards, such as climate change and global warming [1]. The contemporary era is marked by escalating environmental apprehensions and an imperative to curtail carbon emissions. The importance of energy intensity/efficiency has reached unprecedented levels for societies endeavoring to alleviate the repercussions of climate change and hasten the transition to sustainable energy systems. Emissions continue to pose serious risks to human health and the environment, and in this context, countries have developed measures to reduce emissions through energy efficiency regulations [2]. Therefore, optimizing energy consumption is considered a critical priority in achieving sustainable development goals (SDGs) [3, 4]. Energy efficiency stands out as one of the key elements of sustainable development and offers a holistic approach to reducing energy consumption, reducing greenhouse gas emissions, and increasing economic efficiency [5]. As global energy demand is projected to increase steadily in the coming years due to population growth, urbanization, and industrialization processes, improvements in energy efficiency are becoming increasingly critical [6]. Accordingly, energy efficiency measures not only increase ecosystem sustainability but also

promote industrial competitiveness by reducing operational costs [7]. Moreover, energy efficiency is considered as a cost-effective strategy to reduce energy costs, increase competitive advantage, and ensure energy security for businesses, public institutions, and individuals [8].

Artificial intelligence (AI) technologies play a critical role in the effective implementation of energy efficiency and emission reduction efforts. With the recognition that AI can assume a pivotal role in global initiatives aimed at addressing environmental challenges and alleviating climate change, researchers have shifted their focus to its implications for energy and ecological sustainability [9]. Recent developments in AI have provided substantial advancements in tackling environmental dilemmas characterized by uncertainty, complexity, and incompatibility. Noteworthy progress in computational and communication technologies has stimulated the application of AI in enhancing energy efficiency and curtailing emissions. Sophisticated control mechanisms facilitated by computer simulations have allowed for the automation of energy management across diverse urban environments. These innovations yield automated instruments for the design, analysis, simulation, control, and diagnostics of energy systems within urban residential contexts. AI-driven tools are instrumental in elevating grid efficiency and economic viability by promoting the fair allocation of energy resources.

Additionally, in the field of energy management and optimization, it offers advanced authorization while leading to radical transformations in different sectors by analyzing, predicting, and controlling energy consumption models. By using sensors and smart algorithms to operate lighting systems only when needed, it provides significant energy savings. AI algorithms can dynamically adjust temperature settings and airflow speeds based on real-time data, effectively reducing energy consumption while maintaining user comfort [10]. In addition, AI, which can detect failures or inefficiencies by analyzing device data, enables maintenance, and repair processes in time. These technological innovations enable energy systems to operate more efficiently and sustainably [11]. At the same time, it facilitates the structural transformation within the economy from carbon-intensive industries to less carbon-intensive ones, such as services and technology [12].

In industrial contexts, AI is being implemented in processes including manufacturing, refining, and chemical operations to reduce energy consumption while enhancing productivity. It provides a variety of methodologies for the digitalization and optimization of production processes, facilitating substantial energy savings through the identification of inefficiencies via real-time data analytics and offering recommendations for minimizing energy usage. Energy management systems underpinned by AI monitor energy consumption within industrial facilities, concurrently delivering energy management solutions that align with demand and pricing scenarios [13]. Through the proficient management of energy resources, AI not only diminishes energy expenditures but also augments overall operational efficiency.

AI assumes a pivotal role in the domains of urban planning and transportation infrastructure as a distinct application area. It possesses the capacity to optimize transportation routes to curtail fuel consumption and mitigate emissions [14]. It assesses factors including traffic density, road conditions, and vehicle performance to identify optimal routes for vehicles, resulting in environmental advantages such as cost reduction and enhanced air quality [15–18]. AI-supported traffic management has become a new approach that prioritizes environmental sustainability criteria and encourages smart and sustainable growth despite the population density of cities [19]. It plays a significant role in increasing fuel efficiency and reducing emissions by providing real time feedback and effective suggestions to drivers. These technologic strategies facilitate the advancement of sustainable mobility solutions at both the individual and systemic levels. Furthermore, AI is being utilized to avert accidents by boosting the operational efficiency of individual vehicles through the analysis of driving behaviors, engine performance, and maintenance data.

R&D expenditures are similarly widely used to incentivize the development of new technologies and the incorporation of AI to improve energy efficiency. Innovations to improve energy efficiency are measured through the use of patent data. Besides their easy accessibility, patents are considered to be an effective indicator that allows companies to compare their creative or innovative performance in terms of new technologies, new processes, and new products, and are often strongly correlated with other measures of innovation [20, 21]. Indeed, pioneering research by Bound et al. [22] revealed a strong correlation between R&D activities and the number of patents at the firm and industry level. Information and communication technologies (ICTs) play an important role in the transition to a low-carbon electricity system, supporting consumers to make more informed, and efficient energy use decisions [23]. The support and commitment of governments to private and public enterprises in their efforts and innovations plays a critical role in the success of energy efficiency and emission reduction policies. Infrastructure investments, incentive mechanisms, and regulatory frameworks are crucial for the integration of AI technologies into industry. Especially smart meters, a central innovation at the ICT-energy intersection, stand out as a key component of an advanced electricity metering infrastructure that enables high-resolution electricity consumption data to be measured, stored, and transmitted to consumers and utility companies in near real-time.

Global commerce significantly contributes to the dissemination of technologies and the global assimilation of innovations. As the global economy evolves, the mechanisms of international trade and technology transfer becomes vital for environmental sustainability as much as economic development. This mechanism facilitates the transference of essential technologies from developed nations to emerging economies, particularly in the domains of energy efficiency and the mitigation of emissions. The process of technology transfer holds the promise of rendering innovative solutions that enhance energy efficiency and curtail greenhouse gas emissions more accessible across broader geographical areas. Within this context, the prospects afforded by international trade serve as a vital instrument for realizing low-carbon economic growth and the attainment of sustainable development objectives. It enhances efficiency in energy-intensive businesses by facilitating the

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exchange of new technologies between countries. Nonetheless, the implications of trade on energy consumption, along with the diverse economic and environmental capacities of the involved nations, might create possible challenges that may obstruct the achievement of efficiency enhancements and emissions reductions. Despite these obstacles, the question of whether international trade leads to environmental degradation remains a topic of debate. The impact of international trade on the environment is evaluated through three fundamental mechanisms: the composition effect, the scale effect, and the technological effect. According to the scale effect, trade increases economic growth and production scale, leading to higher energy consumption and greenhouse gas emissions, while the composition effect of trade, in line with the principle of comparative advantage, particularly with the increased demand for polluting products, exacerbates environmental degradation. Conversely, the technical effect indicates that trade can diminish greenhouse gas emissions by enhancing competitiveness and facilitating the adoption of eco-friendly technologies. The environmental impact of trade is influenced positively or negatively by the relative significance of these three effects [24]. When the literature is examined, although the main findings of most studies indicate that increasing trade between countries pollutes the environment [25–28], there are also studies showing that increasing trade between countries helps reduce pollution levels [29–33].

The main objective of this study is to analyze in detail the role of AI-based approaches in energy efficiency optimization in the context of trade openness, industrial production, government effectiveness (GE), innovation, and R&D expenditures. The study aims to provide a comprehensive perspective on the transformational potential of AI in energy systems and infrastructures by examining theoretical frameworks, AI applications, advantages, challenges, case studies, and future development areas. This study aims to provide valuable information to energy sector stakeholders and contribute to innovative research in this field by presenting the current status of AI in energy efficiency optimization, while addressing new trends and opportunities. Research on AI impact on energy efficiency is quite recent and this paper used an AI index which includes many aspects of AI field for a comprehensive view on this topic. Moreover, the study investigates the AI impact on energy efficiency by considering industrial production, trade openness, GE, and regulatory quality (RQ) in European Union (EU) countries during 2005–2022 and the estimated model represent the novelty of this study against the existing studies in this area. This period depicts the most important developments in AI field.

The study consists of three main sections. In the introduction section, the theoretical framework is drawn and the results of previous studies on the subject are evaluated. In the second section, the data set used, the method and the obtained findings are presented in detail. In the last section, the comments made in the light of the findings and suggestions for energy policies are shared. With this structure, the study aims to comprehensively discuss the applicability and impact of AI-supported solution proposals in the field of energy efficiency.

2. Methodology and Data

2.1. Methodology. A robust econometric technique that is frequently employed in panel data analysis, the two-step system generalized method of moments (GMM) is particularly useful for dynamic models that involve latent dependent variables and potential endogeneity issues. This approach is based on the foundational work of Arellano and Bond [34] and the subsequent enhancements made by Arellano and Bover [35] and Blundell and Bond [36]. The two-step system-GMM estimator is specifically engineered to mitigate biases in finite samples and guarantee consistency when addressing endogenous regressors, omitted variables, and measurement errors. No AI tools were used for analysis or for writing manuscript.

The system-GMM approach is fundamentally based on the application of both level and differenced equations. The system-GMM estimator enhances efficiency in comparison to the difference-GMM model, particularly when dealing with weak instruments, by integrating these two forms simultaneously.

The dynamic panel model analyzed using two-step system-GMM can be specified as follows (Equation (1)):

$$y_{it} = a y_{it\text{-}1} + X_{it}\beta + \eta_i + \varepsilon_{it}, \tag{1}$$

where

- y_{it}: dependent variable for unit i at time t,
- $y_{it\text{-}1}$: lagged dependent variable,
- X_{it}: vector of explanatory variables,
- η_i: unobserved time-invariant individual-specific effects,
- ε_{it}: idiosyncratic error term.

Endogeneity arises because $y_{it\text{-}1}$ is correlated with η_i, and potentially with ε_{it}. To address this issue, the system-GMM employs instrument variables (IVs) derived from within the dataset itself. Specifically:

1. The first-differenced equation is instrumented using lagged levels of the dependent variable and independent variables.
2. The level equation is instrumented using lagged differences of these variables.

The system of equations for system-GMM is thus:

$$\Delta y_{it} = a\Delta y_{it\text{-}1} + \Delta X_{it}\beta + \Delta\varepsilon_{it}, \tag{2}$$

$$y_{it} = a y_{it\text{-}1} + X_{it}\beta + \eta_i + \varepsilon_{it}. \tag{3}$$

The inclusion of the level equation improves instrument relevance by leveraging the stationarity condition, ensuring more efficient estimates, especially in finite samples.

The two-step GMM estimation process involves:

1. First-step estimation: weights all instruments equally and provides initial coefficient estimates.

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2. Second-step estimation: incorporates a robust weighting matrix derived from the residuals of the first step to improve efficiency. This matrix accounts for heteroskedasticity and autocorrelation in the error terms.

The two-step approach's weighting matrix minimizes the following GMM objective function:

$$Q(\theta) = (Z'\Delta\varepsilon(\theta))'W(Z'\Delta\varepsilon(\theta)), \tag{4}$$

where

- Z: matrix of instruments,
- W: optimal weighting matrix,
- $\Delta\varepsilon(\theta)$: residuals from the first-step estimation.

Unlike static panel methods, system-GMM accommodates lagged dependent variables, enabling the modeling of dynamic relationships that reflect the persistence of the dependent variable and its interactions with explanatory factors over time. This makes the method particularly valuable for examining phenomena where past outcomes influence current behavior. The combination of equations in levels and differences, a key feature of system-GMM, enhances efficiency by reducing the bias associated with weak instruments [36].

Another significant advantage of the two-step system-GMM is its robustness to heteroskedasticity and autocorrelation in the error structure. The second step employs a weighting matrix derived from the residuals of the first step, ensuring consistent and efficient estimates under diverse data-generating processes [37]. Moreover, the method's ability to handle unbalanced panel data makes it particularly suited for real-world datasets, which often contain missing observations or irregular sampling intervals.

Despite these advantages, the two-step system-GMM is not without limitations. One critical challenge is the risk of instrument proliferation, which can occur when the number of instruments becomes excessively large relative to the sample size. This overfitting of endogenous variables undermines the Hansen test of over-identifying restrictions, reducing the reliability of the validity tests [37]. Additionally, while the estimator is asymptotically efficient, small samples may still be prone to finite-sample biases, necessitating caution when interpreting results.

The complexity of the system-GMM also presents practical challenges. Careful attention must be given to the selection and specification of appropriate instruments, as incorrect choices can lead to biased or inconsistent estimates. Furthermore, the methodology is predicated on stringent assumptions, including the lack of second-order serial correlation within the error components and the legitimacy of the instruments employed. Any infringement of these assumptions has the potential to undermine the robustness and credibility of the results obtained.

The two-step system-GMM demonstrates unique advantages in comparison to other methodologies, including fixed effects (FE) and random effects (RE) models. System-GMM improves efficiency by preserving time-invariant variables through the merging of equations in both levels and differences, whereas FE models mitigate the influence of time-invariant variables through differencing, which may lead to the loss of significant information. System-GMM provides a more realistic framework for the analysis of dynamic systems by accommodating endogenous variables and feedback mechanisms, in contrast to ordinary least squares (OLS), which relies on the assumption of strict exogeneity [38].

The dynamic panel data model utilized in this study is specified as follows:

$$\begin{aligned}\text{Enint}_{it} = {} & \beta_0 + \beta_1 L.\text{Enint}_{\text{it-1}} + \beta_2 AI_\text{Index}_{\text{it}} \\ & + \beta_3 \text{IndProdInd}_{\text{it}} + \beta_4 \text{GE}_{\text{it}} + \beta_5 \text{RQ}_{\text{it}} \\ & + \beta_6 \text{TradeOpen}_{\text{it}} + \varepsilon_{\text{it}},\end{aligned} \tag{5}$$

where

- Enint_{it}: energy intensity (dependent variable),
- $L.\text{Enint}_{\text{it-1}}$: lagged energy intensity,
- $AI_\text{Index}_{\text{it}}$: AI Index,
- $\text{IndProdInd}_{\text{it}}$: industrial production index,
- GE_{it}: government effectiveness,
- RQ_{it}: regulatory quality,
- $\text{TradeOpen}_{\text{it}}$: trade openness,
- ε_{it}: error term.

In addition to the dynamic system-GMM estimator, FE, RE, and OLS models are employed to provide robustness checks. These auxiliary models are not the primary estimation method but serve to verify the consistency and direction of the coefficients. While OLS relies on the strict exogeneity of regressors and suffers from bias in the presence of dynamic relationships, FE controls for time-invariant heterogeneity but cannot address endogeneity or lagged dependent variables effectively. RE assumes no correlation between individual effects and regressors [38]. Therefore, these models are presented only for comparative purposes, whereas system-GMM is preferred for its ability to control for endogeneity and dynamic behavior.

2.2. Data. This study employs a comprehensive panel dataset spanning 27 EU countries over the period 2005–2022 to investigate the relationship between AI adoption and energy intensity/energy efficiency. The dataset integrates a variety of variables from reputable international sources, ensuring the robustness, and credibility of the analysis. These variables encompass indicators of AI development, governance, industrial performance, and trade openness, alongside energy intensity as the dependent variable.

The key independent variable, the AI Index, is constructed by the authors using principal component analysis (PCA) to aggregate 15 indicators related to AI development. These indicators include:

- AI-related research metrics, such as the number of published documents, citations, and the H-index on AI topics (sourced from the SCImago Journal Rank, SJR) [39].
- Technological infrastructure indices, including the e-government index, human capital index, and

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Table 1: Components of the AI index.

Variables	Description	Source
Doc	Published documents on AI subject	[39]
Cite	Citation numbers on AI subject	[39]
H	H index on AI subject	[39]
Egovind	E-government index	[40]
Humancapind	Human capital index	[40]
Telinfind	Telecommunication infrastructure index	[40]
Stemg	Percentage of graduates from STEM programs in tertiary education	[41]
Totpat	Total patent applications	[42]
Patperin	Resident applications per million inhabitants	[42]
ICT_exp	ICT sector good export (million $)	[43]
ICT_imp	ICT sector good import (million $)	[43]
ICT_ser_exp	ICT sector service export (million $)	[43]
ICT_ser_imp	ICT sector service import (million $)	[43]
Researchers	Researchers per million people	[44]
Rd_exp	R&D expenditure (%GDP)	[44]

Note: All variables are standardized using z-scores (mean = 0, sd = 1) prior to PCA.

telecommunication infrastructure index, all sourced from the United Nations E-Government database [40].

- STEM education metrics, represented by the percentage of graduates from STEM programs in tertiary education, obtained from the UNESCO Institute for Statistics (UIS) [41].
- Innovation indicators, such as total patent applications and resident patent applications per million inhabitants, sourced from the World Intellectual Property Organization (WIPO) [42].
- ICT-related trade data, including imports and exports of ICT goods and services, derived from the United Nations Conference on Trade and Development (UNCTAD) [43].
- R&D investment metrics, such as researchers per million people and R&D expenditures as a percentage of GDP, sourced from the WDI.

The AI Index, a core component of the study, is estimated using PCA. This technique reduces dimensionality by combining the highly correlated AI-related indicators into a single composite index. The PCA procedure ensures that the AI Index captures the underlying variation in AI development across countries while mitigating multicollinearity issues. Each variable contributing to the index is normalized before aggregation to ensure comparability. Missing data were imputed using the k-nearest neighbors (KNN) algorithm ($k = 5$). All variables were normalized using z-scores to ensure comparability across different scales. The first principal component (PC1) was selected as the composite index, as it explained the majority of the variance (64.35%). The PCA loadings indicate the contribution of each variable to the first principal component. Variables with higher loadings are more influential in determining the composite index. Variables such as patent applications and R&D expenditure had the highest contributions to PC1, highlighting the importance of innovation capacity.

The PCA results reveal that the first component (PC1), which is used to construct the AI Index, is primarily influenced by innovation and digital infrastructure indicators (Table 1). The top contributing variable is the number of resident patent applications per million inhabitants (loading: 0.8915), emphasizing the technological innovativeness of countries. This is followed by the H-index (0.8204), ICT service imports (0.8187), R&D expenditure (% of GDP) (0.8134), and ICT goods imports (0.8035), which reflect the technological dependency and digital integration level of economies. The e-government index (0.7462) and ICT goods exports (0.7304), together with the telecommunication infrastructure index (0.7179) and the volume of AI-related documents (0.6946), also play notable roles. Additional contributors include researchers in R&D per million people (0.6737), citations (0.6621), and the human capital index (0.5950), while the share of STEM graduates (0.4134) and ICT service exports (0.3659) display comparatively smaller loadings.

The dataset also includes several control variables to account for other macroeconomic and governance factors influencing energy intensity: GE and RQ: These governance indicators are sourced from the Worldwide Governance Indicators (WGI) published by the World Bank [44]. Industrial production index (IndProdInd): Indexed to 2010 = 100, this variable reflects the level of industrial activity and is sourced from the United Nations Economic Commission for Europe (UNECE) [45]. Trade Openness (TradeOpen): Measured as the sum of exports and imports as a percentage of GDP, this data is obtained from the WDI (Table 2).

Table 3 reveals significant variability across the key variables. Energy intensity (Enint) averages 3.614 MJ/$2017 PPP GDP, with a wide range (0.97–7.34), highlighting notable disparities in energy efficiency across observations. GE and RQ exhibit

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Table 2: Description of variables.

Variables	Description	Source
Enint	Energy intensity (MJ/$2017 PPP GDP)	[44]
GE	Government effectiveness	[44]
RQ	Regulatory quality	[44]
TradeOpen	Trade openness	[44]
IndProdInd	Industrial production index 2010 = 100	[45]
AI_Index	0–100 scaled AI representative index	Estimated by authors using PCA

Table 3: Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Enint	486	3.614	1.128	0.97	7.34
GE	486	1.0645	0.588	−0.364	2.347
RQ	486	1.156602	0.446	0.135	2.041
TradeOpen	486	123.8394	60.354	45.141	393.141
IndProdInd	486	109.1992	20.351	67.1	286.9
AI_Index	486	0.22463	0.1943	0	1

Table 4: Results of the model.

Variable	Two-step system GMM	One-step system GMM	FE	RE	OLS
L.enint	0.9212 (0.0069)***	0.9168 (0.0216)***	0.7526 (0.0455)***	0.9569 (0.0078)***	0.9569 (0.0078)***
AI_Index	−0.1188 (0.0285)***	−0.1445 (0.0493)***	−1.2396 (0.2867)***	−0.0682 (0.0326)**	−0.0682 (0.0326)**
IndProdInd	−0.0009 (0.0002)***	−0.0009 (0.0003)***	−0.0018 (0.0009)*	−0.0006 (0.0003)*	−0.0006 (0.0003)*
GE	0.0145 (0.0124)	0.0167 (0.0425)	0.0316 (0.0581)	0.0328 (0.0259)	0.0328 (0.0259)
RQ	0.0324 (0.0160)**	0.0373 (0.0362)	−0.0358 (0.0427)	−0.0014 (0.0277)	−0.0014 (0.0277)
TradeOpen	−0.0007 (0.0001)***	−0.0007 (0.0002)***	−0.0035 (0.0010)***	−0.0005 (0.0001)***	−0.0005 (0.0001)***
_cons	0.3383 (0.0493)***	0.3698 (0.1053)***	1.7284 (0.3335)***	0.1730 (0.0463)***	0.1730 (0.0463)***
R-squared (OLS/FE/RE)	—	—	0.8611	0.8467	0.9679
Wald/F-Stat	—	118938.16	526.14	23611.42	3935.24
Hansen test	0.131	0.131	—	—	—
Sargan test	0.082	0.082	—	—	—

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

positive average scores (1.0645 and 1.1566, respectively), indicating generally effective governance and regulation, though their ranges (−0.364–2.347 for GE and 0.135–2.041 for RQ) suggest some countries perform poorly in these areas. Trade openness shows considerable variation (mean: 123.8394, range: 45.141–393.141), reflecting differing levels of global economic integration, while the AI Index has a relatively low mean (0.2246) and high variation, signaling uneven AI development among countries. These patterns underscore substantial heterogeneity in institutional quality, economic openness, and technological advancement across the sample.

3. Results, Findings, and Discussion

3.1. Results and Findings. This study analyzes the determinants of energy intensity using various econometric methods. The findings reveal a strong dependence of energy intensity on its lagged values. The coefficient for lagged energy intensity is estimated to be 0.9212 in the two-step system GMM model, indicating a highly persistent structure over time. This suggests that structural changes in energy intensity occur gradually. Similar findings are observed in the literature, which highlights the inertia of energy intensity over time. The AI Index, representing advancements in AI, exerts a negative impact on energy intensity. In this study, the coefficient for the AI Index is estimated at −0.1188 in the two-step GMM model and −0.1445 in the one-step GMM model. These results imply that AI technologies can enhance energy efficiency by optimizing production processes. This finding aligns with prior studies emphasizing the energy-saving potential of technological innovations (Table 4).

While AI systems indeed consume substantial energy during training and deployment phases, especially in data centers

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and large-scale machine learning infrastructure, our study focuses on the adoption of AI technologies at the macroeconomic level and their integration into energy optimization processes within industries, governance, and smart infrastructure systems.

The AI Index constructed in this study includes components such as R&D investments, patent activity, STEM education, and ICT trade which represent enabling conditions for AI integration in production and governance, rather than solely measuring data center-level hardware deployment.

Moreover, empirical studies [10, 11] show that the net effect of AI adoption on energy systems, especially via smart grid management, predictive maintenance, and intelligent resource allocation, results in reduced operational energy intensity. Thus, despite the essential energy cost of AI systems, the optimization gains in broader industrial and administrative contexts outweigh these costs in the long term, especially when AI is employed as a tool for sustainable transitions.

The industrial production index (IndProdInd) exhibits a negative correlation with energy intensity, suggesting that increases in industrial production slightly reduce energy intensity. Although the coefficients range from −0.0009 to −0.0018, their statistical significance underscores the importance of industrial production in influencing energy intensity. This is consistent with studies that explore the relationship between industrial activity and energy efficiency (Table 4).

Institutional factors, such as GE and RQ exhibit limited impact on energy intensity. The positive effect of GE is not consistent across models, while RQ is significant only in certain estimations. These results suggest that the influence of institutional quality on energy efficiency may depend on specific contexts and implementation levels, as indicated in previous studies.

Trade openness (TradeOpen) demonstrates a robust negative effect on energy intensity, with coefficients ranging from −0.0007 to −0.0005. This finding highlights the role of trade in reducing energy intensity by fostering efficiency gains in production. The results corroborate theoretical arguments linking trade to improvements in energy efficiency.

Evaluating overall model performance, the explanatory power (R-squared) is remarkably high, particularly in the RE model, where the R-squared reaches 0.9679. Furthermore, the validity of the instruments used in GMM models is confirmed by the Hansen and Sargan tests ($p > 0.05$ in both cases). These findings underscore the importance of focusing on technology and trade to reduce energy intensity. In particular, the positive effects of AI applications and trade openness highlight strategic areas that policymakers should prioritize to enhance energy efficiency.

3.2. Discussion. In all models, lagged energy intensity (L.enint) stands out as positive and statistically significant. In the GMM models, the coefficients are between 0.9168–0.9212, indicating a high persistence of energy intensity over time. In the FE model, the coefficient is lower (0.7526), indicating that energy intensity decreases over time, but the effect is strong. This result shows that the energy intensity levels of countries are significantly affected by their past values. In other words, structural factors related to energy use and the technology used in production processes do not undergo radical changes in the short term, and energy consumption habits continue. This finding suggests that long-term strategies are needed for energy efficiency policies to be effective.

The AI index (AI_Index) has a negative and meaningful appearance in the models. Developments in AI technologies increase energy efficiency and reduce energy intensity. In the FE model, the effect is much higher (−1.2396), indicating that AI makes a major contribution to energy efficiency. This finding suggests that AI and digitalization processes increase energy efficiency and reduce energy intensity. Similar results were also observed in the panel data analysis conducted by Matthess et al. [46] on manufacturing sectors in Europe. In the study, it is stated that robot intensity has a negative impact on energy intensity, but it is emphasized that digital capital intensity may increase energy consumption. However, Awogbemi et al. [47] emphasize that AI and digitalization play a critical role in accelerating the transition to sustainable energy and can be a catalyst in achieving SDG 7 (affordable and clean energy) targets. The advantages of AI in areas, such as energy management, forecasting algorithms, and grid optimization contribute to the reduction of energy intensity. AI-enabled production processes, smart energy management systems, and the spread of digitalization make energy use more efficient and ensure less energy consumption per economic output. This result suggests that investing in AI-based technologies and promoting digitalization in industry can be a critical strategy for reducing energy intensity.

Industrial production index (IndProdInd) has a meaningful and negative effect in the models. As industrial production increases, energy intensity decreases, that is, efficiency in production increases. It implies that energy intensity is used more efficiently in large-scale production. This result indicates that economies of scale effect comes into play in industrial production and energy intensity decreases with increasing industrial production. In other words, as the industrial sector grows, firms use more efficient production techniques, energy efficiency increases, and production processes are optimized to consume less energy. In a study covering 40 countries, Voigt et al. [48] show that as industrial production increases, energy intensity decreases thanks to technological advances and structural transformations. Similarly, Shi et al. [49] argue that decreasing energy intensity in the Chinese manufacturing sector is possible through efficiency gains and innovative production processes. In this context, it is suggested that the transition to efficient production technologies in industry should be accelerated and industrial policies should be implemented to reduce energy intensity. The coefficient of GE is positive but statistically insignificant. GE does not have a significant direct effect on energy intensity. However, GE can often have indirect effects in the long run through factors, such as policy stability, energy efficiency incentives, and effective enforcement of regulations, so indirect effects (e.g., regulatory reforms and incentives) should be taken into account.

RQ has a positive and significant coefficient. As RQ increases, energy intensity increases, indicating that some regulations may increase energy consumption. The increase in energy intensity associated with higher RQ, contrary to

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expectations, can be explained by several factors. Compliance costs and inefficiencies arising during the transition process lead firms to invest in energy-intensive technologies to comply with environmental standards, which can lead to an increase in overall energy consumption. Second, firms direct their resources to regulatory compliance rather than to investments that increase energy efficiency, limiting efficiency gains. Furthermore, the simultaneous use of existing and new technologies during the clean energy transition creates a "double burden" that increases energy intensity in the short term. Furthermore, sectoral reallocation effects and the fact that some technological solutions increase, rather than reduce, energy demand are among the factors that contribute to this result. While low-energy-intensity sectors shrink relatively, the dominance of high-energy-intensity sectors can increase energy intensity at the macro level. Finally, some technological innovations (such as carbon capture and storage systems) can increase rather than reduce energy demand, or firms can shift to informal and low-efficiency operations, increasing overall energy intensity. Therefore, RQ may not always increase energy efficiency, but under some circumstances, it can increase energy intensity. Therefore, it is suggested that regulatory policies should be formulated to encourage energy efficiency and carbon footprint reduction. This is in line with the study by Pablo-Romero et al. [50]. In the study, it is stated that regulations applied in some sectors may increase energy consumption instead of encouraging energy efficiency-enhancing investments. In contrast, a study conducted by Chen et al. [51] on manufacturing companies in China between 2003 and 2006 found that stricter energy regulation led to a significant decrease in energy intensity and encouraged companies to switch from fossil fuel use to cleaner energy alternatives. There are two main explanations for this result. First, energy regulations encourage firms' R&D investments, contributing to the development of technological innovation, a critical element in reducing energy intensity. Second, these regulations lead to a reallocation of energy use among firms. While firms with higher energy efficiency may consume more fossil energy in absolute terms due to their larger production scale, they also use less energy per unit of output, leading to a decrease in average energy intensity. Using a forecasting framework, Lin and Li [52] show that environmental governance constraints have the potential to reshape China's energy structure, leading to reductions in CO_2 emissions and coal consumption. Chen et al. [53] examine the effectiveness of the 11th Five-Year Plan (FYP) in controlling water pollution. Their results suggest that pollution-intensive activities declined in regions subject to stricter regulations, while they increased in less regulated areas.

Trade openness shows in the models a negative and significant coefficient. Energy intensity decreases with increasing trade openness, which helps to spread energy-efficient technologies over world trade. This finding suggests that deregulation of commerce reduces the energy intensity. In their study of the Chinese economy, Wang et al. [54] claim that trade openness reduces energy intensity and helps green technologies to proliferate. Ren et al. [55] also argue that trade can help to lower carbon emissions. Implementing open economy policies helps countries to import advanced energy-efficient machinery and equipment from worldwide markets and acquire such technology. This result shows that worldwide trade helps to spread energy-efficient technologies; so, countries should create their trade policies to improve energy efficiency. The results show that the use of AI, industrial output, and trade openness favorably affects energy intensity; yet, some legislative actions may worsen energy intensity.

4. Conclusion

This study conducts a comprehensive panel data analysis of OECD and emerging countries to ascertain the primary determinants affecting energy intensity. The investigation rigorously analyzes the effects of AI and digitalization on energy intensity, the correlation between industrial production and energy consumption, the significance of governance indicators, such as governmental efficacy and RQ, and the influence of trade openness on enhancing energy efficiency. This study's findings provide policy suggestions aligned with global SDGs. The findings show that energy intensity shows a great degree of persistence over time; so, long-term changes should take front stage in energy strategies instead of temporary fixes. AI and digitalization appear to significantly reduce energy intensity, highlighting the necessity for extended investments in digital technologies throughout the industrial and energy sectors. Due to economies of scale and enhanced manufacturing methods, energy intensity often diminishes as industrial output grows. However, it has been noted that specific regulatory strategies may unintentionally increase energy usage. Trade openness helps to transfer green technologies and reduces the energy intensity. The results mostly support the energy policies pushed by global institutions. The International Energy Agency [56] underlines that including AI and automation into the industrial sector would help to improve energy efficiency and lower carbon emissions. The United Nations Sustainable Development Report (UN, 2023) [57] underscores that digitalization and international trade will facilitate the attainment of SDG 7 (affordable and clean energy) and SDG 9 (industry, innovation, and infrastructure). The World Bank [44] contends that political entities should enhance incentive frameworks for green technologies and advises that initiatives designed to increase energy efficiency support enduring economic growth. In this framework, it becomes increasingly imperative to formulate energy policies that are supported by digital and AI, to advance efficient production paradigms within the industrial sector, to recalibrate regulatory policies to foster green transformation, and to devise trade openness strategies that enhance access to green technologies.

This paper assesses the impacts of technology, industry, governance, and trade policies on energy intensity comprehensively and provides recommendations to enhance the effectiveness of energy policies. Green growth, industrial digitization, and increased trade integration are essential for achieving global SDGs. Consequently, it is imperative for governments and international organizations to formulate comprehensive and enduring programs to enhance energy efficiency.

In this context, it is important that policy recommendations are not limited to a general level, but are concretized based

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on specific actors. First, the European Commission should strengthen the implementation tools of the European Green Deal, which focuses on energy efficiency, with AI and digitalization-based mechanisms. In this context, it should develop an EU-level monitoring system that will track comparative energy efficiency indicators among member states and coordinate AI-based control processes. National industry ministries, on the other hand, should design incentive mechanisms that facilitate the transition of small and medium-sized enterprises to digital energy management systems. Through tax breaks, subsidies, and public–private partnerships, digitalization in industry will gain momentum, and the efficiency gains created by economies of scale will be reflected in energy intensity in a more systematic way. National energy agencies should develop technical guidelines, standards, and capacity-building programs for AI-supported energy efficiency applications, taking sectoral differences into account; they should also institutionalize these technologies through pilot projects. International organizations (IEA, UN, World Bank, etc.) should increase financial and technical support for green transformation projects based on AI and digitalization; they should also strengthen cooperation platforms that facilitate technology transfer between developed and developing countries. Finally, national governments should recalibrate their legislation and focus on improving governance quality to prevent existing regulatory policies from causing unexpected increases in energy consumption. This actor-based differentiation will contribute to the field-level impact of energy efficiency strategies by enhancing not only the theoretical and empirical contributions of the study but also its applicability for policymakers.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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