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The Innovation Paradox in the United States: Why AI Innovation Outperforms Green Technology in Driving Energy Efficiency

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ABSTRACT

The United States energy sector exhibits an innovation paradox whereby considerable financial commitments to green technology innovation (GTI) have not translated into proportional gains in energy efficiency, notwithstanding the nation's prominent position in green patent generation. This study evaluates the relative efficacy of artificial intelligence (AI) innovation compared with conventional GTI in advancing energy efficiency across the United States (U.S.) over the period 1990–2022. Employing autoregressive distributed lag (ARDL) bounds testing in conjunction with rolling window estimation techniques, the analysis assesses the respective impacts of GTI and AI innovation, while incorporating government intervention and the proportion of renewable electricity within the energy mix as control variables. The empirical findings identify a pronounced innovation paradox: AI-based innovation exerts a stronger and statistically significant effect on energy efficiency enhancement relative to traditional GTI. By delivering robust quantitative evidence on the comparative technological drivers of efficiency improvement, this study advances the expanding body of scholarship concerning the technology–environment interface. The results carry important implications for the formulation of sustainable development policies and the strategic prioritisation of innovation pathways.

1. Introduction

As the world's largest economy and the second-highest carbon emitter, the U.S. faces mounting pressure to enhance energy efficiency, which remains central to mitigating climate change and sustaining the competitive position of advanced economies such as the U.S. A principal indicator used to assess this dimension is gross domestic product per unit of energy consumption, commonly termed energy intensity, which captures the extent to which economic output is generated relative to energy input [69]. Between 2000 and 2023, the energy intensity of the U.S. economy declined by 41% [32]. Notwithstanding this improvement, aggregate energy consumption, domestic production, and

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energy imports expanded markedly during 2001–2025 [7], reinforcing the strategic necessity of sustained efficiency gains to secure long-term economic and environmental benefits.

Despite substantial capital allocation towards GTI, the U.S. continues to underperform relative to several developed counterparts in energy efficiency outcomes. The 2022 International Energy Efficiency Scorecard published by American Council for an Energy-Efficient Economy (ACEEE) ranked the U.S. tenth globally, whereas France, United Kingdom, Germany, and China occupied the first, second, third, and eighth positions respectively (see Figure 1) [4]. Although the U.S. accounts for the second-largest volume of green technology patent applications World Population [78], and has directed approximately $60 billion towards low-carbon initiatives, grid-scale storage, fossil-fuel and clean energy supply, and end-user technologies [33], alongside more than $11 billion in public climate finance in 2024 [63], these financial commitments have primarily supported renewable deployment, commercialisation of green technologies, and technological substitution. Consequently, the broader transformative capacity of AI to advance energy efficiency has not been fully realised.

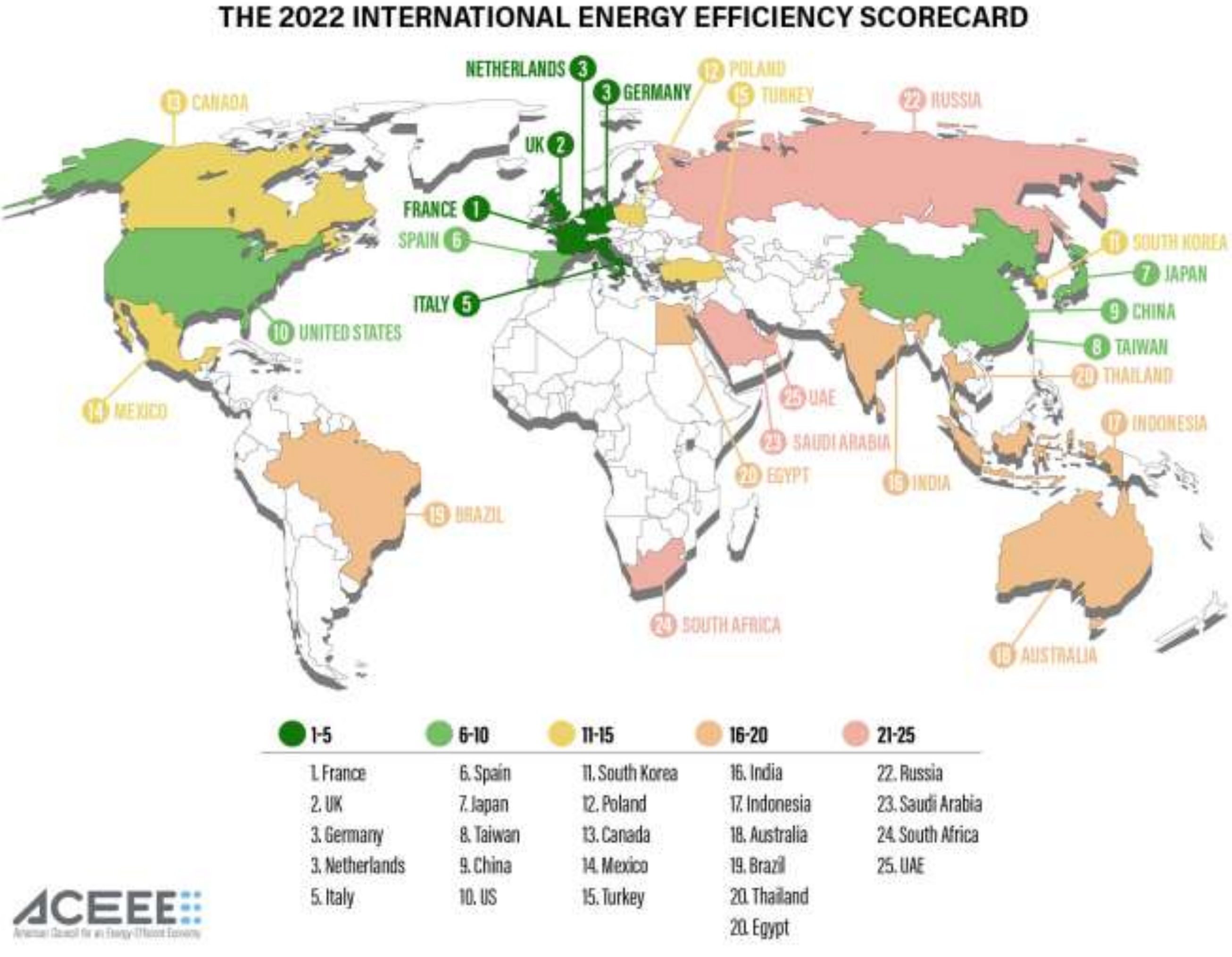

Fig.1: International Energy Efficiency Scorecard [4]

Although the transformative capacity of AI is frequently understated, a growing body of scholarship identifies AI as a critical mechanism for advancing energy efficiency beyond the capabilities of conventional GTI approaches [79],[27]. AI facilitates predictive maintenance, real-time operational optimisation, enhanced decision-making, and intelligent control across energy infrastructures, thereby strengthening system-wide efficiency [14; 37; 51]. AI-enabled systems have improved solar energy administration and increased the operational performance of smart grids [13]. Evidence further indicates that AI enhances energy resilience and supports carbon mitigation objectives, while generating broader efficiency gains across multiple sectors [36]. Whereas traditional technologies largely concentrate on infrastructure replacement and incremental support mechanisms, AI introduces optimisation capabilities that augment existing energy management systems. Nevertheless, systematic empirical investigation into the optimisation paradigm of AI within the U.S. context remains limited. Addressing this deficiency is essential for determining whether AI offers superior efficiency gains capable of advancing national energy intensity performance.

The U.S. represents a salient case of the innovation paradox in the energy domain, defined as a condition in which substantial technological investment yields lower-than-anticipated performance outcomes [15]. Despite extensive expenditure on research and development, leadership in green patent generation, and investment in renewable energy technologies and climate-oriented innovations, including AI applications, advanced solar systems, electric vehicles, and carbon capture technologies [32],[77],[63], national energy efficiency, measured as GDP per unit of energy use, remains comparatively modest relative to other advanced economies [5]. For instance, although the U.S. possesses one of the largest portfolios of green patents globally [77], this technological advantage has not translated into commensurate leadership in efficiency performance. Comparable patterns have also been observed in parts of Europe, where innovation has not consistently delivered expected efficiency gains [6]. Policy emphasis in the U.S. has primarily focused on expanding green patenting, incentive structures, and green technology outputs [26],[53],[55], while comparatively limited attention has been devoted to AI-driven optimisation strategies. This imbalance suggests a critical research gap, namely whether AI can generate superior efficiency outcomes relative to prevailing policy instruments. Although patent activity is widely treated as a proxy for innovation-induced efficiency improvements [46],[17], such measures may fail to capture the distinct optimisation effects attributable to AI. Moreover, AI possesses significant cost-reduction potential that can further reinforce efficiency improvements [30]. A more comprehensive understanding of these additional benefits may guide policymakers in determining the strategic integration of AI within national energy systems.

Existing empirical contributions Gamtessa and Olani [25],Pata et al. [54],Peñasco [55],Sibt-e-Ali et al. [62] and Teng et al. [67] have predominantly examined conventional determinants of energy efficiency, including energy pricing mechanisms, GDP expansion, income growth, financial incentives, subsidies, and regulatory interventions. However, limited attention has been directed towards evaluating emerging technological pathways, particularly AI, as a primary driver of efficiency enhancement. Much of the prior literature concentrates on microeconomic variables and neglects the broader structural association between AI transformation and aggregate energy efficiency, which influences national energy intensity. Empirical evidence concerning the role of AI within the U.S. energy sector therefore remains insufficient.

Furthermore, methodological constraints in earlier studies obscure the dynamic characteristics of technology adoption. While some analyses incorporate cross-sectional dimensions to capture adjustment processes [23; 64; 76], they often lack long-term temporal depth. Several studies focus on relatively short observation windows of five to ten years [11; 55], thereby restricting insight into long-run adoption cycles and lifecycle efficiency gains. This study addresses these limitations by employing an extended 33-year time horizon. Additionally, prior research has not fully utilised time-series approaches capable of distinguishing between pre-digital and digital transformation eras in assessing AI diffusion. Conventional econometric frameworks adopted in earlier works [27; 38; 45; 56] frequently assume homogenous innovation effects [15], thereby overlooking the possibility that AI innovation may exert qualitatively distinct impacts compared with GTI. This methodological oversight constitutes a key gap that the present study seeks to resolve.

This research offers comprehensive empirical evidence comparing two major innovation pathways designed to enhance U.S. energy efficiency. By analysing data spanning 1990–2022 through the ARDL modelling framework, which mitigates spurious regression risks and accommodates mixed orders of integration [1; 31; 48], the study demonstrates that AI innovation exerts a stronger efficiency-enhancing effect than GTI. The findings indicate that GTI, in the absence of complementary AI-based optimisation, is unlikely to generate optimal efficiency outcomes, thereby offering a potential explanation for the persistent innovation paradox in the U.S., where high investment and patent activity coexist with relatively modest efficiency gains [4; 34]. Structural stability diagnostics confirm the durability of the estimated relationships over time Ahmed et al. [3], including during major disruptions such as the 2008 global financial crisis and the COVID-19 pandemic. Additional robustness verification using Fully Modified Ordinary Least Squares and Dynamic Ordinary Least Squares further substantiates the long-run results.

Following this introductory section, Section 2 elaborates the theoretical foundations and reviews relevant literature concerning selected determinants, identifying key limitations in prior scholarship. Section 3 justifies the time-series econometric framework, detailing unit root procedures, ARDL bounds cointegration testing, and stability assessment. Section 4 presents the empirical findings, while Section 5 concludes with policy implications and directions for future research.

2. Literature Review

2.1 Theoretical Foundation: Innovation Pathways and Energy Efficiency

AI may be conceptualised within the framework of general-purpose technology theory, which contends that certain foundational technologies possess broad applicability, progressive improvement potential, and extensive spillover effects across sectors [14]. AI fits this characterisation, given its diffusion across multiple industries and its functional capabilities, including real-time analytics, predictive maintenance, automated decision processes, and systemic optimisation, all of which generate substantial productivity and efficiency gains [14],[37],[52]. Within energy systems, AI contributes to enhanced operational performance and efficiency enhancement. Panel evidence covering 52 countries over two decades indicates that AI mitigates energy vulnerability by strengthening governance quality, encouraging GTI, and supporting structural transformation [27]. Similarly, Slimani et al. [63], employing the PROCESS approach across 24 developed economies, demonstrate that AI, operating through the channel of renewable energy transition, improves environmental performance outcomes.

Despite its broad diffusion and classification as a general-purpose technology, AI has received comparatively limited attention within innovation policy debates at the national level in the U.S. [70][23]. Public policy instruments in the U.S. have predominantly prioritised technology-specific mechanisms such as tax incentives, subsidies, and direct green investments. However, given AI’s cross-sectoral optimisation capacity, a stronger policy emphasis on AI-driven efficiency mechanisms is warranted. Beyond the general-purpose technology perspective, academic discourse has also distinguished between technological replacement and system optimisation as alternative innovation pathways influencing environmental performance [18][42]. Technological replacement typically involves upgrading legacy systems with cleaner and more energy-efficient alternatives. In environmental economics, this approach is associated with substituting carbon-intensive infrastructures with lower-emission technologies [72]. The Porter hypothesis partially supports this view by proposing that environmental regulation can stimulate firms to adopt innovative technologies that enhance sustainability and competitiveness [64]. Nevertheless, replacement

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strategies frequently entail substantial research and development expenditures and capital adjustment costs.

In contrast, system optimisation emphasises integrating advanced technologies such as AI into existing infrastructures to improve efficiency without complete technological substitution. Evidence from Kirikkaleli et al. [38], using U.S. time-series data and the ARDL bounds estimation framework, suggests that AI-related investment has measurable environmental implications, underscoring the need to evaluate its efficiency dynamics comprehensively. Path dependence theory further clarifies why established innovation regimes may dominate over emerging technologies such as AI [59]. Historical policy choices, infrastructure commitments, and subsidy allocations can entrench prevailing technological systems, generating institutional lock-in effects that impede the diffusion of alternative optimisation-oriented innovations [66].

2.2 Empirical Literature on Technology–Environment Relationships

Recent empirical contributions document favourable associations between GTI and environmental performance, particularly where green patents and related innovations contribute to carbon abatement and improved efficiency outcomes. Cao et al. [16], undertaking a comparative assessment across G7 economies, conclude that GTI plays a central role in advancing renewable energy adoption and delivering ecological gains through emission reduction. Similarly, Feng and Xu [24], applying the MMQR framework to G7 countries, demonstrate that environmental patents and green technological adoption significantly enhance sustainability performance. In parallel, evidence indicates that the deployment of AI-enabled industrial robots across 62 countries has reduced fossil fuel consumption by raising labour productivity and facilitating structural transformation [45]. Biggi et al. [9] further argue that AI functions as a catalytic general-purpose technology within the domain of green intelligence, exerting a stronger influence on environmental innovation outcomes. Nonetheless, these investigations often rely on cross-sectional methodologies or recent datasets, thereby limiting their capacity to capture long-term dynamics and exposing findings to potential cross-sectional bias.

Although research attention towards AI applications within energy systems has increased, such contributions remain fragmented across disciplinary boundaries. Studies by W. Zhang et al. [80], Y. Wang et al. [71], and X. Zhang et al. [81] indicate that AI adoption enhances energy efficiency and accelerates renewable energy diffusion. W. Zhang et al. [80] further report a U-shaped relationship between industrial robot installation and firm-level financial performance. Fang et al. [23], employing panel data from 51 U.S. states, identify a statistically significant positive effect of AI on energy transition processes. Technical-oriented investigations also demonstrate that AI strengthens grid security [59], improves production efficiency [40], optimises energy generation and resource allocation [47], enhances demand forecasting, and reduces energy waste. However, these analyses are predominantly technical in nature and often lack comprehensive macroeconomic evaluation. Many studies are based on pilot initiatives or limited case studies rather than nationwide empirical assessments [35][60], which constrains generalisability. While Boston Consulting Group [12] estimates that large-scale AI deployment could reduce global greenhouse gas emissions by 5–10% by 2030, signalling substantial systemic potential, rigorous long-term empirical evidence focusing exclusively on the U.S. remains scarce.

2.3 Technology Diffusion Theory and Technology-Specific versus Neutral Policies

The pace and breadth of innovation diffusion critically influence the environmental consequences of technological change, since the shift from obsolete, inefficient systems to advanced sustainable alternatives depends on the speed and extent of adoption. Technology diffusion theory explains this process by emphasising perceived relative advantage, observability, complexity, compatibility, and trialability as determinants shaping adoption decisions across populations [41][53]. In the context of GTI, diffusion is often constrained by high upfront capital requirements, insufficient infrastructural readiness, and regulatory complexity, all of which impede large-scale efficiency gains [61].

By contrast, AI-based energy optimisation software can generate cost efficiencies within existing infrastructural frameworks, thereby lowering adoption barriers [30]. Policy design in the U.S. has predominantly relied on technology-specific instruments to stimulate innovation, including state-level tax incentives for designated technologies, direct energy subsidies aimed at efficiency improvements [28], and renewable energy support schemes [16]. Such targeted mechanisms may accelerate deployment within specific technological domains [43]. However, evidence from dynamic panel data covering 38 countries, including the U.S., indicates that technology-neutral instruments, particularly carbon pricing, can provide broader market incentives that encourage innovation and the uptake of energy-efficient solutions. Despite this potential, such neutral policy approaches have been comparatively underutilised in facilitating AI-driven efficiency transitions. Moreover, much of the existing evidence relies on cross-sectional or panel methodologies without comprehensive time-series analysis, and often overlooks heterogeneous effects across different technological categories.

2.4 Research Positioning and Gap Identifications

The extant literature highlights several substantive gaps. Although AI is broadly recognised as a critical enabler of energy efficiency [77][72][59], and GTI has been examined independently as a determinant of efficiency outcomes [77][16][24], direct comparative evaluations of AI innovation and green patent-based innovation remain scarce. Despite extensive financial commitments directed towards green patent applications, low-carbon initiatives, clean technological development, climate finance, and fossil fuel supply management to sustain efficiency performance [32][75][63], limited attention has been devoted to assessing the relative effectiveness of distinct innovation pathways, particularly AI-driven optimisation within energy systems. While prior studies acknowledge the beneficial contributions of AI in areas such as energy production, grid enhancement, real-time analytics, predictive maintenance, and process optimisation [57][40][47][14][37][52], broader macro-level implications for national energy efficiency in the U.S. have not been sufficiently examined.

Methodologically, much of the existing scholarship relies on cross-sectional frameworks, short-term analytical horizons, and conventional econometric specifications, thereby constraining the ability to evaluate country-specific dynamics, long-run structural adjustments, and heterogeneous innovation effects [27][55][56][23][45][38][64][10]. Although Gamtessa and Olani [25], Pata et al. [54], and Peñasco [55] suggest the presence of an innovation paradox in the U.S. despite substantial investment, few studies have rigorously tested whether AI-based optimisation strategies outperform GTI in generating sustained energy efficiency improvements. This study addresses these deficiencies by systematically comparing AI-driven optimisation with green patent-based innovation in influencing U.S. energy efficiency. A time-series econometric framework is employed to capture long-term dynamics and mitigate cross-sectional bias associated with short-horizon analyses. By explicitly distinguishing AI from conventional patent-driven innovation, the research develops a comparative analytical structure to inform optimal innovation policy choices in the U.S. Furthermore, structural stability diagnostics are incorporated to account for dynamic adjustments and ensure robustness of the estimated relationships over time.

Table 1
Recent Literature on AI Innovation and Green Technology Innovation

Authors	Observed Samples and Methodologies	Remarks (Findings Related to this Paper or Establish any Relevant Arguments)
[45]	Sample Covered: 62 Countries, Including the U.S. Methodology: Two-Stage Least Squares Method	AI-automated industrial robots significantly reduce the level of fossil fuel use by improving industrial labour productivity and industrial structure upgrading.
[38]	Sample Covered: U.S. Only Methodology: ARDL Bound Estimator	AI investment exhibited nonlinear effects on environmental quality, resulting in a higher ecological footprint.
[27]	Sample Covered: 52 Countries Methodology: Panel Data Analysis	AI's capability of reducing energy vulnerability through improving governance effectiveness, promoting green technology, and facilitating structural improvements
[63]	Sample Covered: 24 Developed Countries Methodology: PROCESS Methodology	AI, mediated by the renewable energy transition, contributed to improved environmental performance.
[23]	Sample Covered: 51 States of the United States Methodology: Panel Data	AI has a significant positive impact on the energy transition.
[16]	Sample Covered: G7 Countries Methodology: Longitudinal Examination	GTI is crucial for achieving renewable energy and ensuring ecological benefits through carbon reduction.
[24]	Sample Covered: G7 Countries Methodology: MMQR	The adoption of environmental patents and green technologies is crucial for achieving substantial results in environmental sustainability.
[44]	Sample Covered: 38 Countries, Including the USA Methodology: Dynamic Panel Data Analysis	Carbon pricing can motivate markets to innovate and adopt new, energy-efficient technologies.
[26]	Sample Covered: Canada Methodology: Panel Vector Autoregression	The study found that increasing energy cost through carbon pricing motivated energy efficiency investment in Canadian Industries.
[55]	Sample Covered: USA Methodology: Fourier Cointegration Test	The study found that higher income is associated with economic growth, such as GDP growth, and is influential in increasing energy efficiency alternatives, including renewable energy investment in the USA.
[56]	Sample: UK Methodology: Discrete Choice Econometric Techniques	Additionally, policy instruments such as financial subsidies, incentives, and regulations in the United Kingdom persuaded households to adopt energy efficiency measures.
[11]	Sample Covered: 9 EU Countries Methodology: MMQR	It suggested R&D investment in greener technologies can drive energy efficiency through cutting CO2 emissions.
[11]	Sample Covered: China Methodology: Descriptive Statistics	The study suggested that R&D investment in greener technologies can drive energy efficiency by reducing CO2 emissions. Robots driven by renewable energy contributed to energy efficiency and pollution reduction.

3. Research Methodology

3.1 Data Description

This study employs annual time-series data for the U.S. covering the period 1990–2022 to evaluate the extent to which energy efficiency can be enhanced through AI innovation, GTI, renewable electricity integration into the power grid, and government intervention. The selected 33-year horizon captures major technological shifts, regulatory transformations, and innovation cycles, thereby enabling identification of long-run equilibrium relationships while ensuring adequate temporal variation for rigorous econometric estimation. The dependent variable, EEF, is defined as real economic output per unit of primary energy consumption. This indicator reflects the economy's ability to generate output with reduced energy input, incorporating both technological advancements and structural economic adjustments. Sustained improvements in EEF can yield economic cost savings, mitigate environmental externalities, and strengthen energy security through reduced energy dependence, which explains its growing policy relevance.

Annual data are obtained from established international databases, including World Bank World Development Indicators, World Intellectual Property Organization, and Organisation for Economic Co-operation and Development, all recognised for methodological consistency and reliability. The principal explanatory variable, LAIP, measures AI-related patent activity and represents the accumulated knowledge stock associated with AI applications in the U.S. It is constructed using annual patent publications classified under AI-related technological domains reported by WIPO. Due to distributional skewness, LAIP is transformed into logarithmic form to stabilise variance and permit elasticity-based interpretation. This proxy captures innovation intensity in AI and reflects commercially oriented technological developments with market applicability [57]. Beyond representing innovation output, AI holds transformative potential to optimise existing technological infrastructures and improve energy efficiency processes when effectively deployed. Additional explanatory variables, along with their definitions, measurement approaches, and data sources, are summarised in Table 2. The formal model specification is presented in Eq. (1), and the empirical estimation procedure is outlined schematically in Figure 2.

EEF= f(LAIP, GTI, GIN, RES) (1)

Table 2:
Description and Sources of Data

Study Variables	Economic Meaning	Measure	Data Origins
Energy Efficiency (EEF)	Real output generated per unit of primary energy	$\text{EEF} = \frac{\text{GDP (2021 PPP \$)}}{\text{Total primary energy use}}$	WDI [74]
AI Patents (LAIP)	Knowledge stock specific to AI	Annual WIPO patent publications in AI-related technology in the USA; ln transformed	WIPO [75]
Green Technology Innovation (GTI)	Flow of environment-related inventions	Annual count of environment-related patent families (CPC Y-02); ln transformed	OECD [50]
Government Intervention (GIN)	Size of the public sector	General government final consumption expenditure as % of GDP	WDI [74]
Renewable Electricity Share (RES)	Substitution toward renewable electricity	$\text{RES} = \frac{Renewable\ electricity\ output}{\text{Total } electricity \text{ output}} * 100$	WDI [74]

3.2 Methodological Framework

The study initiates diagnostic assessment by applying advanced unit root tests designed to accommodate potential structural breaks, which can otherwise lead conventional methods to incorrectly fail to reject the unit root null hypothesis. Both the augmented Dickey–Fuller (ADF) test [20] and the Phillips–Perron (PP) test [58] are employed to detect endogenous breakpoints within the time series.

The ADF test accounting for structural breaks is formally expressed in equation (2):

$$\Delta y_t = \alpha + \beta y_{t-1} + \gamma DU_t + \delta DT_t + \sum_{i=1}^{k} \phi_i \, \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

Where DU_t is a dummy variable capturing a level shift, and DT_t captures a trend break at an endogenously determined break point. This approach is particularly important in the context of energy and innovation, as these sectors often experience structural shifts arising from policy reforms, technological advances, or economic disturbances, phenomena that are typically evident in long-term datasets [55].

After conducting unit root tests, the study applies the ARDL bounds cointegration approach proposed by [57] to assess the existence of long-run relationships, as mixed integration orders frequently arise in energy–economic analyses. A key advantage of the ARDL methodology is its capacity to accommodate variables of differing integration orders, whether I(0), I(1), or fractionally integrated, without imposing uniform integration requirements. This flexibility is particularly suited to energy economics, where innovation, efficiency, and policy-related variables often exhibit heterogeneous persistence that standard unit root assumptions may obscure. Furthermore, the ARDL framework mitigates endogeneity concerns by including lagged values of both dependent and independent variables, thereby producing more consistent and reliable coefficient estimates when explanatory variables are potentially correlated with the error term. The null hypothesis of no cointegration (H_0: $\alpha_1 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$) is also tested primarily via the bounds test, which employs asymmetric critical values developed by [57] and updated by [39] to account for deterministic components, model specifications, and finite-sample properties. To reinforce the findings, the analysis is supplemented with Engle and Granger's [21] two-step residual-based cointegration procedure, alongside the Wald test [76] to evaluate long-run coefficient constraints. The integration of these methods strengthens the robustness of inferences regarding the presence of cointegrating relationships within the dataset. The ARDL bounds testing framework is formally specified in equation (3):

$$\Delta EEF_t = \alpha_0 + \alpha_1 EEF_{t-1} + \beta_1 LAIP_{t-1} + \beta_2 GTI_{t-1} + \beta_3 GIN_{t-1} + \beta_4 RES_{t-1} + \sum_{i=1}^{m} \gamma_1 \Delta EEF_{t-i} + \sum_{i=1}^{m} \gamma_2 \Delta LAIP_{t-i} + \sum_{i=1}^{m} \gamma_3 \Delta GTI_{t-i} + \sum_{i=1}^{m} \gamma_4 \Delta GIN_{t-i} + \sum_{i=1}^{m} \gamma_5 \Delta RES_{t-i} + \varepsilon_t \quad (3)$$

Where m represents the optimal lag length determined by the chosen information criterion of our study, and Δ denotes the first difference operator. Upon establishing potential cointegration, the study estimates the error correction model (ECM) to disentangle short-run dynamics from long-run equilibrium relationships, as expressed in equation (4):

$$\Delta EEF_t = \alpha_0 + \sum_{i=1}^{m} \gamma_1 \Delta EEF_{t-i} + \sum_{i=1}^{m} \gamma_2 \Delta LAIP_{t-i} + \sum_{i=1}^{m} \gamma_3 \Delta GTI_{t-i} + \sum_{i=1}^{m} \gamma_4 \Delta GIN_{t-i} + \sum_{i=1}^{m} \gamma_5 \Delta RES_{t-i} + \lambda ECT_{t-1} + \varepsilon_t \quad (4)$$

Where ECT_{t-1} represents the error correction term derived from the long-run cointegrating relationship and λ captures the speed of adjustment toward the long-run equilibrium. The error correction coefficient is expected to be negative and statistically significant, reflecting the speed at which deviations from long-run equilibrium are corrected over time.

4. Results and Discussion

The descriptive statistics reported in Table 3 indicate substantial variation among the key variables, while Figure 2 illustrates overall trends throughout the 33-year study period. EEF ranges from 5.733 to 11.172, reflecting marked transitions in energy efficiency over time. LAIP follows the expected growth trajectory, particularly accelerating after 2010, consistent with trends in AI development [70], and is likely to continue expanding given near-doubling of AI-related data centre investments since 2022 [19]. In contrast, GTI exhibits limited variability, with a standard deviation of 0.292 and near-zero skewness, indicating steady innovation flows in contrast to the rapid expansion observed in AI. GIN and RES display higher volatility, with standard deviations of 0.868 and 3.629 respectively, and among the highest kurtosis values, a pattern also visible in their time-series trends.

Table 3
Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
EEF	33	7.985	1.694	5.733	11.172	0.370	1.974
LAIP	33	8.837	1.258	6.593	10.119	-0.630	1.787
GTI	33	7.697	0.292	7.102	8.167	0.186	1.863
GIN	33	14.956	0.868	13.714	16.808	0.448	2.246
RES	33	12.116	3.629	7.422	20.273	1.095	3.008

Examination of multicollinearity, presented in Table 4, indicates minimal concern, as all individual variance inflation factor (VIF) values are below 10, and the mean VIF is 3.51, well within the conventional threshold of 5 [29].

Table 4
VIF Result

Variable	VIF	1/VIF
GTI	6.57	0.152124
LAIP	3.15	0.317426
RES	2.87	0.348656
GIN	1.47	0.682125
Mean VIF	3.51	

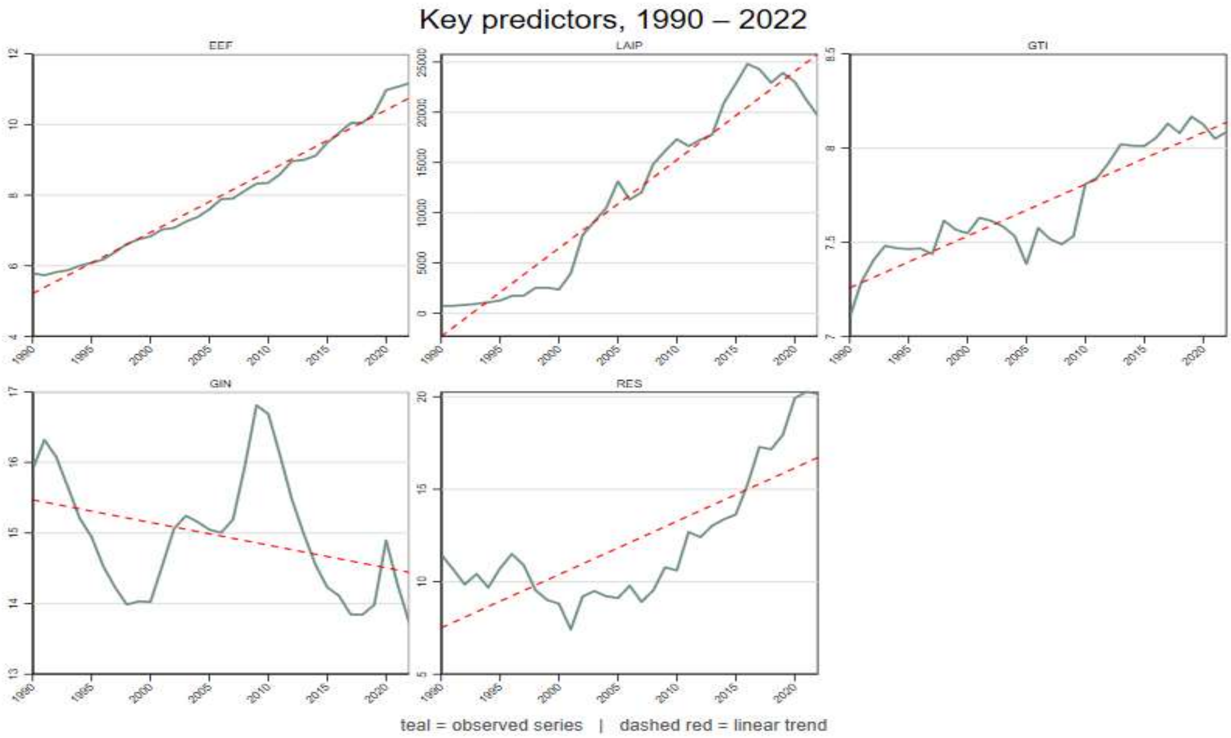

Fig.2: Time Series Plot with OLS Trend Line

Following the descriptive analysis and examination of inter-variable correlations, stationarity was assessed using the enhanced ADF and PP unit root tests. Results, presented in Table 5, confirm mixed integration properties across the variables, thereby supporting the application of the ARDL bounds testing framework. All explanatory variables, except GIN, are nonstationary at level but achieve stationarity after first differencing, consistent with I(1) behaviour commonly observed in economic time series. The presence of mixed integration orders validates the choice of ARDL methodology, which accommodates variables of differing integration without imposing uniform assumptions [57]. Comparable outcomes were observed in the PP test.

Table 5
Unit Root Test Results

Variables	Equation Includes	ADF		PP		Remarks
		Level	**First Diff.**	**Level**	**First Diff.**	
EEF	Trend	-1.4737	-8.0945***	-2.0370	-6.3810***	I (1)
LAIP	Trend	-0.3822	-4.3382***	-0.0741	-4.7803***	I (1)
GTI	Trend	-1.9804	-4.2330***	-2.4382	-5.9916***	I (1)
GIN	Constant	-2.646*	-3.210**	-1.557	-3.375**	I (1)
RES	Trend	-0.9156	-4.9457***	-1.1976	-6.4268***	I (1)

Notes: ***, **, and * denote rejection of the null hypothesis at 1%, 5% and 10% respectively.

Subsequently, model selection criteria were applied, as summarised in Table 6. The optimal model was initially identified based on the lowest AIC and BIC values. Although there was deliberation regarding BIC minimisation, the final selection was guided by the model exhibiting the lowest RMSE, thereby ensuring superior predictive accuracy. The chosen specification is ARDL (1,0,0,2,0).

Table 6
Robustness Checks and Model Diagnostics

Test/Specification	Statistic	RMSE
Model Selection Criteria		
ARDL (1,0,0,2,0) AIC	-39.293	0.1152
ARDL (1,0,0,2,0) BIC	-27.821	
ARDL (1,0,0,1,0) AIC	-36.98	0.1249
ARDL (1,0,0,1,0) BIC	-28.186	

Table 7 summarises the primary results, highlighting the innovation paradox that challenges conventional assumptions regarding the drivers of energy efficiency. The evidence indicates that AI innovation delivers substantially greater efficiency gains than traditional GTI. Specifically, LAIP exhibits a highly significant long-run coefficient of 0.787, implying that a 1% increase in AI patent intensity is associated with approximately a 0.79% improvement in energy efficiency. In contrast, GTI demonstrates a smaller coefficient of 0.749, which is statistically insignificant, signalling that conventional green technology investment contributes less effectively to efficiency outcomes. This disparity suggests a misalignment in U.S. innovation policy, which has historically prioritised green R&D and patenting as key instruments for efficiency enhancement.

The superior impact of AI reflects its capacity to optimise energy systems via advanced machine learning and data analytics, enabling more effective resource utilisation across sectors [73]. Recent initiatives by the U.S. Department of Energy illustrate that AI can reduce operational costs by up to 15% and increase productivity by 10% in energy applications. Similarly, ADNOC's AI-driven energy efficiency measures generated $500 million in value and cut carbon emissions by approximately one million tonnes in 2023 alone [76]. GIN shows a positive but statistically insignificant effect, suggesting that government intervention can support energy efficiency, consistent with findings from [8] in the EU context. In New York, Meng et al. [78] reported a 14% reduction in energy consumption over four years following policy implementation, aligning with our finding of gradual policy contributions. By contrast, RES exhibits a significant positive coefficient of 0.27 at the 1% level, indicating that renewable energy expansion provides complementary improvements to overall energy efficiency.

Table 7:
ARDL Results

Variable	ARDL (1,0,0,2,0)
Long-Run Coefficient	
LAIP	0.787***
GTI	0.749
GIN	0.076
RES	0.273***
Short-Run Coefficient	
ΔGIN (-1)	.149**
ΔGIN (-2)	-.100
Model Diagnostics	
Observations	31
ECT (-1)	-0.176**
R-Squared	0.436
Adj. R-Squared	0.265

***Notes:** *, *, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The significantly negative ECT coefficient reported in Table 7 confirms the presence of long-run cointegration, indicating that roughly 17.6% of any deviation from the long-term equilibrium is corrected within a single year. Cointegration test results, summarised in Table 8, provide nuanced evidence of long-run relationships among the variables. The F-statistic of 5.328 exceeds 5% and 10% upper bounds for I(1), supporting the existence of cointegration; however, the associated t-statistics fall between the I(0) and I(1) bounds at the 10% level. Such outcomes are not unusual in energy economics studies with limited sample sizes and likely reflect the mixed integration properties revealed by the unit root analysis. Considering the F-statistic, we confirm the presence of long-run cointegration.

Table 8
Cointegration Tests

Test	Statistic	Critical Values			Decision
		10%	5%	1%	
Pesaran Bounds Test (Case III)					
F-Statistic	5.328	I (0): 2.752	I (0): 3.359	I (0): 4.831	Evidence of
		I (1): 3.967	I (1): 4.743	I (1): 6.610	cointegration based on
T-Statistic	-3.274	I (0): -2.575	I (0): -2.935	I (0): -3.680	the F-statistic
		I (1): -3.680	I (1): -4.104	I (1): -4.976	

***Notes:** *, *** denote significance at the 5% and 1% levels, respectively.

Model diagnostics, reported in Table 9, indicate overall robustness. The Breusch–Godfrey LM test confirms the absence of serial correlation, residuals are normally distributed, and ARCH effects are absent. While residual heteroskedasticity is present, the residuals remain stationary. Stability tests using CUSUM and CUSUMQ further demonstrate strong parameter constancy over the sample period. Figure 3 illustrates that the CUSUM statistic remains well within the 95% confidence bounds throughout, with zero boundary crossings, indicating that the core relationships are stable across multiple economic and policy regimes. Notably, stability persists during major disruptions, including the 2001 dot-com bubble, the 2008–09 financial crisis, and the early COVID-19 period, confirming the resilience of the estimated model.

Table 9
Diagnostic Tests

Diagnostic Test	Test Statistic	P-Value	Remarks
Serial Correlation (Breusch-Godfrey LM, lags 1)	χ^2 (1) = 0.041	0.840	No Serial Correlation
Serial Correlation (Breusch-Godfrey LM, lags 2)	χ^2 (2) = 2.956	0.228	No Serial Correlation
Heteroskedasticity (Breusch-Pagan)	χ^2 (1) = 5.26	0.022	Heteroscedastic Errors
Normality (Skewness-Kurtosis)	χ^2 (2) = 0.57	0.753	Normally Distributed Residuals
ARCH Effects (LM test, lags 1)	χ^2 (1) = 0.597	0.440	No ARCH Effects
Unit Root in Residuals (ADF)	Z(t) = -6.141	<0.01	Stationary Residuals (Cointegration Confirmed)

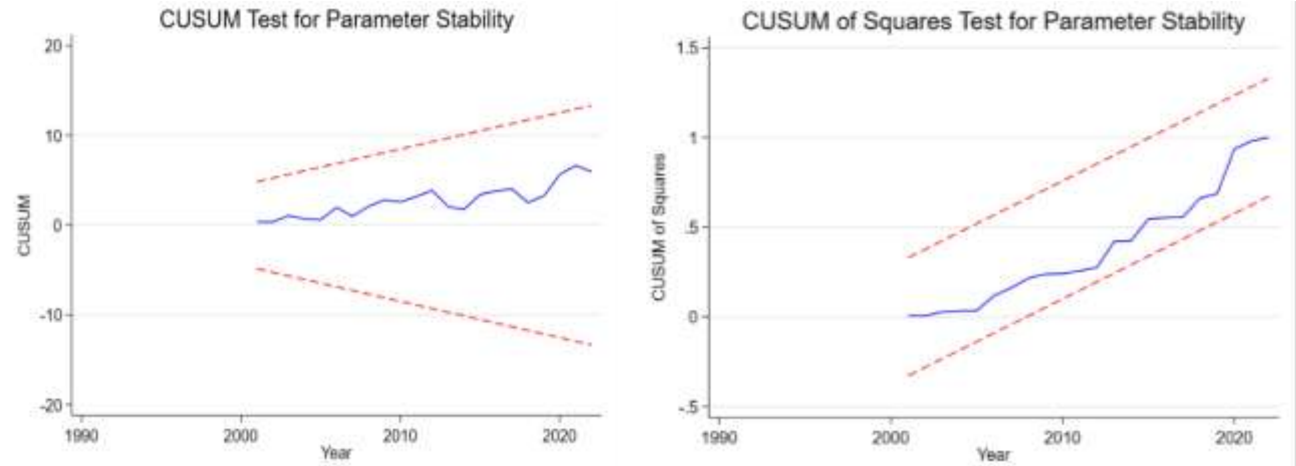

Fig.3: Model Stability and Variance Stability Plots Via the CUSUM and CUSUMQ Squared Tests

An anomaly emerges between the two innovation pathways in their impact on U.S. energy efficiency. Despite substantial national investments in GTI, AI-driven innovation demonstrably yields greater improvements in total energy output efficiency. To substantiate this result, the study employs Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS), as reported in Table 10. Both estimation techniques corroborate the innovation paradox: LAIP exhibits a dominant effect relative to GTI in FMOLS, while DOLS estimates show a comparable pattern, with both results statistically significant at the 1% level. RES maintains a consistently positive and significant contribution to energy efficiency, whereas GIN exhibits a negative effect, suggesting that government intervention alone does not substantially enhance energy efficiency outcomes in this context.

Table 10
Robustness Check with DOLS and FMOLS

Variable	FMOLS β	FMOLS t	DOLS β	DOLS t
LAIP	0.78***	15.87	0.65***	22.92
GTI	0.56*	1.66	0.66***	8.15
GIN	-0.05	-1.02	-0.02	-0.61
RES	0.22***	11.71	0.14***	11.10

***Notes:** *, *** denote significance at the 5% and 1% levels, respectively.

5. Conclusions and Policy Recommendations

5.1 Summary of the Key Findings

Despite considerable investment in GTI, AI innovation emerges as the principal driver of energy efficiency improvements, surpassing the impact of traditional green patents. Using a 33-year dataset spanning 1990–2022 and advanced time-series econometric techniques, this study provides critical insights into the innovation efficiency paradox, including the magnitude of effects, policy stability during crises, speed of adjustment, the complementary role of renewable energy, asymmetries in innovation impacts, and misalignments in U.S. energy policy. The analysis confirms the existence of the innovation paradox, demonstrating that AI contributes more substantially to U.S. energy efficiency than GTI. Long-run and robustness checks indicate that increases in AI innovation enhance energy efficiency more effectively and reliably than GTI. In contrast, GTI exhibits an insignificant contribution, underscoring its comparatively limited role in driving efficiency gains. Concerning policy resilience, the relationships among AI, GTI, GIN, RES, and energy efficiency remain stable across major disruptions, including the COVID-19 pandemic and the 2008 financial crisis. Finally, the findings highlight a policy misalignment, as U.S. energy strategies have historically prioritised green technology patenting over AI-driven innovation, potentially underutilising AI's transformative potential.

5.2 Policy Implications and Recommendations

Based on the findings that AI innovation outperforms GTI in driving energy efficiency, the Federal Government should consider rebalancing its investment priorities. Although the U.S. has historically invested heavily in low-carbon technology innovation, including grid storage, fossil fuel power, clean supply, end-user technologies [30], and public climate finance [63], reallocating a portion of these resources toward AI deployment could generate larger efficiency gains at the national level. Policy support should also include targeted incentives for AI innovation. For instance, President Trump's announcement of a $92 billion investment in AI and energy represents a promising step toward efficiency improvements [68], but a meaningful share of these funds should be explicitly directed toward fostering AI innovation. Policymakers could implement instruments such as AI adoption tax credits, Small Business Innovation Research (SBIR) programs, and regulatory sandboxes to accelerate deployment [22]. Priority sectors for AI-driven innovation could include transportation (37%), industry (35%), and residential (15%), which the EIA [2] identifies as the largest energy consumers, ensuring early interventions generate more rapid efficiency gains.

While AI-driven innovation demonstrates superior efficiency outcomes, this study does not advocate the elimination of existing green technology programmes; rather, it recommends integrating AI optimisation with GTI. Evidence indicates that AI can enhance the performance of other green energy technologies, creating synergistic effects that improve overall energy efficiency [17; 30; 40; 49]. To maximise the benefits of AI-driven optimisation, the Federal Government should adopt a long-term strategic approach, recognising that substantial time is required for innovation-to-implementation cycles to yield measurable efficiency improvements. A multiyear plan with dedicated, protected funding across AI's lifecycle would facilitate sustainable optimisation of energy systems. Additionally, a roadmap outlining projected efficiency gains alongside practical evaluation mechanisms can guide strategic AI deployment, ensuring the highest possible improvements in national energy efficiency [72].

5.3 Limitations and Future Directions

This study relies on aggregate national-level data for the U.S., which constitutes a notable limitation as it may conceal sectoral and regional heterogeneity. Variations across industries or economic sectors could generate differential impacts that the aggregate approach fails to capture. Similarly, using patent counts as a proxy for innovation may understate the actual deployment of energy-efficiency measures, as many AI solutions are implemented through nonpatentable software or proprietary applications that nonetheless contribute substantially to system optimisation. The study does not account for differential effects across income groups, firm types, or regional contexts, limiting understanding of whether the benefits of adopted technologies are equitably distributed.

Endogeneity concerns and overlapping program timelines may also constrain the analysis, although the relationships observed historically appear stable. Future innovations or breakthroughs in AI or GTI could alter these dynamics. While AI demonstrated resilience during disruptions such as the COVID-19 pandemic and the 2008 financial crisis, similar crises could reduce innovation activity. Moreover, the study does not incorporate direct implementation costs for AI versus GTI due to data limitations, preventing full cost–benefit analysis. Although the 33-year annual dataset provides a comprehensive view, it may overlook intra-year dynamics, and future breakthroughs, such as quantum AI or fusion energy, could modify established relationships.

Future research should prioritise sector-specific analyses using disaggregated data to identify high-return AI applications. Firm-level microdata could uncover adoption barriers, heterogeneous effects by firm size or region, and inform targeted incentives, enabling a broader understanding of operational energy-efficiency gains. Detailed industry-level investigations could highlight sectors generating the highest returns, facilitating policy prioritisation. Comparative international studies may assess the generalizability of AI-driven energy efficiency outcomes and explain why some developed countries outperform the U.S. despite substantial investments in green technologies. As AI comprises a suite of technologies—including machine learning, natural language processing, computer vision, and robotics—future research should evaluate technology-specific impacts on energy efficiency. Finally, integrating emerging technologies, such as AI-enabled renewable systems, and leveraging real-time data can better capture evolving dynamics, supporting adaptive and responsive policy frameworks.

Author Contributions

Conceptualization: E.L. and M.F.I.; Data curation: M.F.I.; Formal analysis: E.L. and M.F.I.; Investigation: E.L. and M.F.I.; Software: E.L. and M.F.I.; Methodology: E.L. and M.F.I.; Project administration: E.L. and M.F.I.; Validation: E.L.; Visualization: E.L. and M.F.I.; Writing – original draft: E.L. and M.F.I.; Writing, review and editing– E.L.; Funding Acquisition: E.L.; Supervision: E.L.

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Data Availability Statement

The dataset analyzed during the current study is available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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