IJEMD-SS, 5 (1) (2026) https://doi.org/10.54938/ijemdss.2026.05.1.723

International Journal of Emerging Multidisciplinaries: Social Science

Research Paper
Journal Homepage: www.ojs.ijemd.com
ISSN (Online): 2958-0277

Unveiling the Determinants of Environmental Sustainability in 11 DAC Countries: Evidence from the Load Capacity Factor, Driscoll–Kraay Estimation, and Machine Learning

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Abstract

Achieving environmental sustainability alongside economic growth remains major policy problems for advanced economies. While existing literature has largely investigated carbon emissions or ecological footprint indicators, relatively few studies have assessed environmental sustainability though the load capacity factor (LCF). This study examines the relationships between information and communication technology (ICT), renewable energy consumption (REC), economic growth (lnGDP), industrial value added (lnIVA), trade openness (lnTO), and environmental sustainability across 11 selected DAC economies from 2000-2024. Before estimating the empirical interplay, the study conducts 2^nd^-generation panel diagnostic tests for CSD, slope heterogeneity, unit roots, and long-run cointegration. The Driscoll-Kraay estimator is then employed to account for CSD, serial correlation, and heteroscedasticity. In addition to the panel econometric analysis, Random Forest (RF), Decision Tree, Lasso, Ridge, and Linear regression models are used to investigate predictive performance and potential nonlinear relationships. The DK estimates indicate that all explanatory variables are positively associated with LCF, although the association of ICT and REC shows comparatively modest. Among the machine-learning The Random Forest model perform best, achieving R^2 of 0.6356 and an RMSE of 0.4906. The results suggest that digital expansion and clean energy transitions, sustainable trade integration, and green industrialization should be accompanied by context-specific environmental sustainability to enhance long-run environmental quality.

Keywords: Load Capacity Factor, Information and communication technology, Renewable energy consumption, Driscoll–Kraay estimator, Random Forest, DAC countries

1. Introduction

Environmental sustainability has become a crucial policy priority in response to the rising challenges of climate change, and ecological degradation. Despite advances in digital technologies, renewable energy, and environmental governance, ecological conservation remains a major challenge for both developed and developing nations (IPCC, 2023; United Nations, 2023). In response, policymakers increasingly seek approaches that can achieve multiple objectives such as fostering economic prosperity, technological development, and environmental quality. Against this background, selected DAC economies provide a crucial setting for investigating the drivers of environmental quality because of their relatively advanced economic structures, digital transformation and green energy policies, and environmental policy framework.

Environmental quality has traditionally been measured using indicators like CO^2 emissions and ecological footprint. Though, these indicators only look at certain elements of environmental quality. Recent studies have proposed the LCF as a broader measure of environmental quality because it captures ecological footprint and biocapacity (Pata & Isik, 2021). Meanwhile, ICT has become a significant enabler of sustainable growth, including the optimization of energy use, technological innovation, and smart resource management (Balsalobre-Lorente et al., 2025). Furthermore, renewable energy consumption (REC) can contribute to environmental sustainability by decreasing dependence on fossil fuels and thus declining ecological pressure (Bekun et al., 2021). TO, lnGDP, and lnIVA may also influence environmental sustainability via productivity improvement and structural transformation. Though, the environmental implications of these influences may depend on technology development and environmental policy conditions (Yunxia, and Yuqing, 2025).

Despite the increasing literature on environmental sustainability, several gaps remain in the research. First, most empirical studies continue to rely on carbon emissions or ecological footprint, while few examine LCF. Second, previous studies have predominantly focused on BRICS and other developing and emerging economies, with comparatively limited attention to selected DAC economies. Third, previous studies often examine these factors separately, limiting a comprehensive assessment of the combined role of ICT, REC, lnGDP, lnIVA and TO in environmental sustainability. These gaps highlight the need for further empirical investigations.

Figure 1 presents the LCF trends across 11 selected DAC economies from 2000 to 2024. The findings reveal clear differences in LCF across economies. Germany, Norway, Denmark, and the Netherlands record higher LCF values, while Australia and Sweden show relatively lower LCF values. Switzerland shows greater fluctuations, mainly after 2015. Overall, the figure displays the substantial cross-country variation in environmental sustainability.

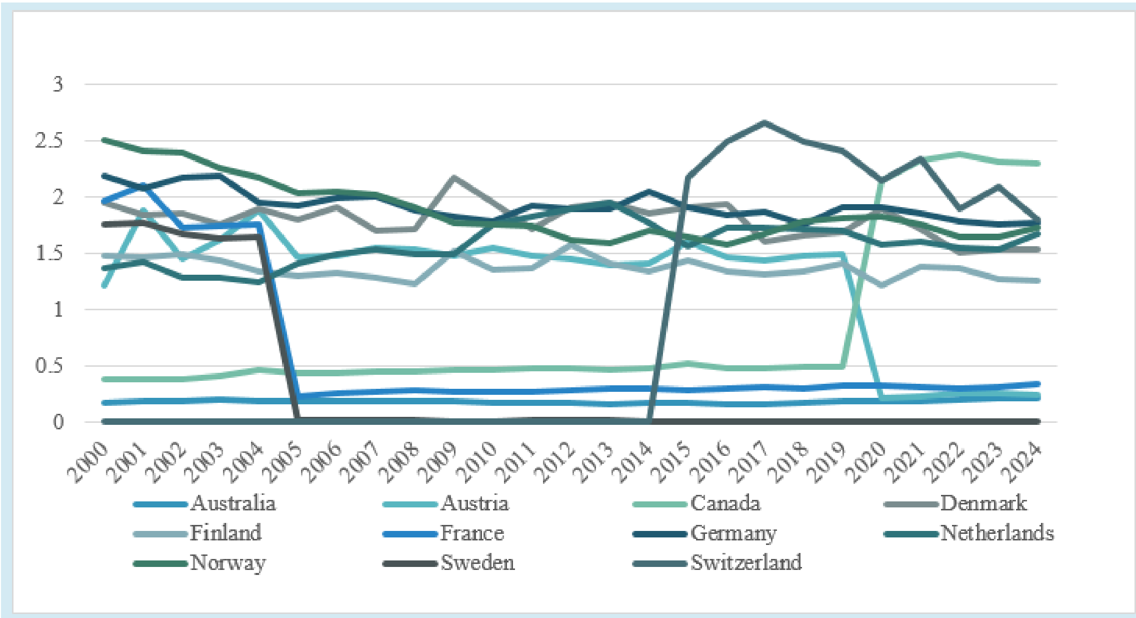

Figure 1: *LCF Trends in DAC Countries*

To address these gaps, this study explores the interconnection between ICT, REC, lnGDP, lnIVA, lnTO and environmental sustainability in selected 11 DAC countries for the period 2000-2024. To account for CSD, heteroscedasticity and serial correlation using the DK approach.

This study contributes to the current literature in three ways. First, using LCF as a inclusive measure of environmental quality. Second, it provides new empirical evidence for selected DAC economies, which have received limited attention in previous studies. Third, it jointly investigates ICT, REC, lnGDP, lnIVA, lnTO within combine framework and complements the econometric analysis with RF and other machine-learning approaches to give broader insights into the factors connected with environmental quality.

The rest of this study is outlined as follows: In Section 2, the literature review and/or development of research hypotheses are presented. The data, variables, econometric model and estimation approach are described in Section 3. Empirical findings are presented and discussed in Section 4, including robustness analysis. Lastly, Section 5 summarizes the study and offers policy recommendations and avenues for further research.

2. Literature Review

2.1. ICT and Environmental Sustainability

The use of ICT has played an important role in improving resource use, production efficiency, and technological innovation, thus contributing to sustainable development. The Ecological Modernization Theory states that technological advancements can separate economic development from environmental harm in three ways: cleaner production, energy-efficient technologies, and environmental governance. Digital technologies such as artificial intelligence, cloud computing, the Internet of Things, and smart manufacturing enable real-time environmental monitoring, and production efficiency (Zafar et al. 2025). Therefore, ICT is considered a key enabler in achieving environmental sustainability (Nasser, and Abdelkaoui, 2025) and contributing to economic growth as well. Digitalization has been gaining a lot of attention due to its environmental benefits. ICT enhances information sharing, contributes to the smartness of transportation systems, electricity grids, and renewable energy integration, and, as a result, increases energy efficiency, thereby reducing ecological pressure. Digitalization has also been proven to improve environmental performance through various mechanisms, including green innovation, cleaner production, and more efficient resource utilization, in recent studies (Pu. 2025). Similarly, digital transformation strengthens environmental innovation and sustainable production, especially in countries with strong digital infrastructure and efficient institutions (Xia et al., 2025).

However, not all the benefits of ICT are environmental. As digital services continue to grow, so does the demand for electricity, energy use in data centers, and the amount of e-waste, potentially negating some of its environmental benefits. In this way, the environmental footprint of ICT relies on the energy mix, digital infrastructure's efficiency, use of renewable energy, and environmental governance quality (Wu and Akram,2026). Recent research also reveals that digitalization could lead to rebound effects: as a result of digitalization, overall energy demand could rise again without cleaner production technology or sustainable energy systems. To summarize, there is currently some evidence that ICT contributes to environmental sustainability, but this will be influenced by other factors such as renewable energy, technological innovation, and institutional quality. Although there is a lot of literature available, environmental quality is normally expressed in terms of carbon emissions or ecological footprint, with only a small number of studies using LCF, which gives a wider picture of environmental sustainability. Further, although DAC countries are leaders in digital transformation and environmental governance, there is still limited evidence of their role. These gaps warrant an investigation of how ICT can help improve environmental quality using LCF.

2.2. Renewable Energy Consumption and Environmental Sustainability

The use of REC is considered one of the main pillars of environmental sustainability, as it helps decarbonize energy systems, mitigate greenhouse gas emissions, and move away from fossil fuels. Energy Transition Theory states that switching from fossil fuels to renewable energy resources, improves ecological sustainability and supports long-term energy security. The International Energy Agency (IEA, 2024) forecasts that the use of renewable electricity will more than double by 2030 (Shi and Zhao, 2025; Gul et al. 2026). The environmental benefits of renewable energy are well established from a body of empirical evidence. Unlike carbon emissions or ecological footprint, the LCF reflects both ecological demand and ecosystem capacity, resulting in a more holistic measure of environmental sustainability. Within this framework, Pata (2024) demonstrated the many positive effects of renewable energy on environmental sustainability. Ullah et al. (2023), Danish and Ulucak (2023) and Bekun et al. (2024), also reported similar findings, stating that renewable energy helps to alleviate ecological stress by decreasing reliance on fossil fuels and enhancing environmental conditions.

However, the environmental advantages of renewables vary from country to country. They are contingent on the quality of renewable energy infrastructure, technological advances, financial development, electricity-grid capacity, and institutional quality. The environmental benefits are generally larger in countries with well-developed renewable energy systems, and smaller or delayed in countries with less developed systems. Accordingly, some studies reported that the impacts are different or asymmetric across countries (Muhammad et al., 2025). Further, recent evidence suggested that the contribution of renewable energy should not be considered alone but also take into account the broader economic and institutional environment, as a successful energy transition relies on these conditions as well (Kabeyi, and Olanrewaju, 2022; Hassan et al., 2024).

In DAC countries, renewable energy should play an even larger role since these economies have more advanced technologies, environmental institutions, and financial resources to speed up the clean energy transition. Most past studies, however, have used carbon emissions and ecological footprint as environmental indicators and have been limited to developing economies. Empirical evidence on the LCF of DAC countries remains limited, indicating the need for more research.

2.3.Trade Openness and Environmental Sustainability

Although trade openness can have either positive or negative impacts on the environment, it is one of the most controversial factors to explain environmental sustainability (Le, et al. 2016). The Pollution Halo Hypothesis, however, argues that international trade leads to cleaner production and technological innovation, and improvements in environmental standards, as a result of technology transfer and international competition (Taylor, 2004; Ali, and Wang, 2024).
Empirical evidence shows that the impacts of trade openness on the environment are mostly context-dependent, as revealed by recent empirical evidence based on the LCF. Research indicates that trade can also promote environmental sustainability by promoting technology diffusion, production efficiency, green innovation, and other mechanisms, especially in countries that have well-developed institutions and technological capabilities (Ali et al., 2025). However, other studies suggest that growing trade can lead to higher transportation emissions, industrial activity, energy use, and resource extraction in nations with poor environmental governance and fossil-fuel-intensive production processes (Ning et al., 2026).
These mixed results suggest that the effect of trade on the environment is not only related to trade liberalization, but also to the extent of institutions, technological change, industrial structure and environmental policies. For developed countries like DAC countries, in which environmental standards are generally high and cleaner technologies are prevalent, trade openness positively affects environmental sustainability via the Pollution Halo mechanism. However, future reductions in car production and transportation can reduce environmental advantages if the gains in production and transportation costs outweigh the improvements in technology. Although the relationship is growing in interest, relatively few studies focus on trade openness and ICT in conjunction with other factors such as GDP growth and industrial development, especially for DAC countries, and consider the topic based on the LCF. This motivates the present study.

2.4.Economic Growth and Environmental Sustainability

Economic growth is a key pillar of environmental sustainability, as it can have both positive and negative effects on the environment. Rapid economic growth can expand industrial production, energy consumption, and natural resource use, putting pressure on the environment. Meanwhile, increased income also provides the means to invest in cleaner technologies, enforce stronger environmental laws and regulations, and increase production efficiency. Overall, the empirical results support the premise that the interplay among growth and environmental quality is nonlinear, as more advanced economies can achieve environmental sustainability through technological progress, investing in renewable energy, and implementation of environmental legislation (Choi, et al., 2010; Arif et al., 2023). But the signs are still not conclusive. Other research reports that the growth process still exacerbates environmental pressures due to the growing need for energy and products, which exceeds the progress of technology, especially in economies that are dependent on fossil fuels (Mutezo et al., 2021). However, research on developed countries indicates a positive relationship between income level and green innovation, sustainable infrastructure, and cleaner production, leading to an increase in the LCF (Deng et al., 2024). Recent studies also support the notion that the environmental impact of economic growth is not limited to growth but rather depend on institutional quality, technological advances, renewable energy utilization, and environmental governance (Wahab et al., 2024).

The linkages among GDP growth and environmental quality are, in general, very context-dependent. Countries in the DAC group are advanced in their institutions and technological capabilities, and have ambitious climate policies; they are expected to improve their environment through innovation and efficient use of resources during economic growth. However, there is limited empirical evidence for the DAC countries regarding the use of the LCF and thus the need for additional studies.

2.5.Industrial Value Added and Environmental Sustainability

Industrial development is a crucial factor in environmental sustainability as it influences energy consumption, resource efficiency, and technological advancements. Industrialization has traditionally been linked to high usage of fossil fuels, environmental pollution, and resource depletion. However, the relationship between industrial development and environmental quality has changed with the adoption of Industry 4.0, digital manufacturing, automation technologies, and cleaner production technologies. Sustainability of production and energy use has recently become increasingly relevant in modern industries, as industrial development can take place without compromising environmental issues through the application of energy-efficient production processes, circular economy practices, waste reduction, and green innovation (Li, et al. 2023).

The Ecological Modernization Theory suggests that as industries innovate new technologies, they can be more efficient in production, use resources less intensively, and reduce their environmental impact. AI, digital monitoring, and smart manufacturing technologies enable companies to leverage energy efficiently, minimize waste, and improve their environmental impact without compromising productivity (Aithal, and Aithal, 2023). Therefore, the potential of industrial value added can be positive for environmental sustainability, provided by technological development and proper environmental management. There is empirical evidence that largely confirms this for developed economies. Research indicates that such sustainable industrialization helps address environmental issues through cleaner production, integration of renewable energy, and technological advancements (Bekun et al., 2023). The results from developing countries are, however, mixed, with evidence of increased fossil fuel use, less robust environmental laws, and resource-intensive production (Tan et al., 2025; Zafar, et al. 2026). The differences indicate that the impact of industrialization on the environment is affected by technological capability, institutional quality, industrial structure, and the nature of the environmental policy.

Interest in this relationship has increased, but comparatively few studies discuss the value added of industries based on the LCF, especially for advanced countries like the DAC countries. Moreover, a small body of literature also examines the linkage of industrial development, along with ICT, REC, lnTO, lnIVA and lnGDP, in a single framework. Filling these gaps will provide a more complete picture of sustainable industrial development.

3. Methodology

3.1.Data and Sample

This study examines the determinants of environmental sustainability in 11 selected economies of the Development Assistance Committee (DAC) from 2000–2024. The analysis employs a balanced panel dataset comprising 11 DAC economies, resulting in 275 country-year observations. Detailed definition, and all variables measurements reports in Table 1.

TABLE 1: VARIABLE DEFINITIONS

Variable	Description	Measurements	Sources
lnLCF	Load Capacity Factor	Biocapacity/Ecological Footprint	Global Footprint Network
ICT	Information and Communication Technology	% Individuals Using Internet	WB
REC	Renewable Energy Consumption	% of Total Final Energy Consumption	WB
lnTO	Trade Openness	% of GDP	WB
lnGDP	Economic Growth	Natural Log of GDP per capita	WB
lnIVA	Industrial Value Added	Natural Log	WB

3.2.Model Specification

3.2.1. *Linear Econometric Model*

Following theoretical foundations and empirical literature, environmental sustainability is specified as a function of digitalization, renewable energy adoption, trade openness, economic growth, and industrialization. The baseline log-linear econometric panel model is formulated as follows:

$$lnLCF_{it} = \alpha_0 + \beta_1 ICT_{it} + \beta_2 REC_{it} + \beta_3 lnTO_{it} + \beta_4 lnGDP_{it} + \beta_5 lnIVA_{it} + \epsilon_{it} \quad (1)$$

where i represents country and t represents time. α_0 denotes the unobserved baseline constant, while $\beta_1 - \beta_5$ denote the elasticity parameters of the respective explanatory variables and ϵ_{it} is the stochastic error term that captures unobserved factors affecting environmental sustainability.

3.2.2. *Non-Parametric Machine Learning Model: Random Forest*

To complement the linear parametric specification and capture potential non-linear interactions, non-monotonic patterns, and high-order interaction effects among the covariates, a non-parametric Random Forest (RF) regression ensemble is specified:

$$\widehat{ln\,LCF}_{it} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(X_{it}) \tag{2}$$

Where, B represents the total number of decision trees in the ensemble, $T_b\,(X_{it})$ is the numerical prediction from the b_th individual decision tree, and X_{it} is the complete vector of explanatory predictors variables included in RF model:

$$X_{it} = [\ ICT_{it}, REC_{it},\ ln\,TO_{it}, ln\ GDP_{it} ln\ IVA_{it},\ Country_i Year_t\ ] \tag{3}$$

Unlike linear estimators, the ensemble structure predicts outcome values by aggregating outputs across bootstrapped decision trees without imposing pre-determined distributional functional forms.

3.3.Estimation Strategy

An empirical analysis is carried out in a sequential estimation procedure. To summarize the data and identify interconnections among variables we applied descriptive statistics and pairwise correlation analysis is first. Next, VIF are calculated to check for multicollinearity. Then applied CSD tests and the Pesaran–Yamagata slope heterogeneity test are undertaken before the estimation to test for CDS and slope heterogeneity. The second-generation (CIPS) unit root test addresses stationarity while considering CDS. The Westerlund (2007) error correction-based cointegration test is used to test for long-run equilibrium interplay between the variables. The following diagnostic tests are then performed: The Modified Wald test of Heteroscedasticity and the Wooldridge test of Serial correlation. Because of Heteroscedasticity, serial correlation, and CSD, the DK estimator is used as the main estimation method, as it yields valid standard errors in these situations. Finally, an econometric model using the Random Forest (RF) regression technique is estimated to supplement this linear econometric model. K-fold cross-validation is used to tune the number of trees (B) and the number of features to consider for splitting (mtry) to prevent overfitting. Permutation Feature Importance and Partial Dependence Plots (PDPs) are applied to gain model interpretability and the explanatory power of each variable in the ensemble framework, respectively.

4. Results and Interpretation

The descriptive statistics of the study variables are shown in Table 2a, and the data are representative of a balanced sample of 275 observations from 11 DAC countries for the period 2000–2024. The results suggest adequate variation in all variables; therefore, the dataset is suitable for panel data analysis. Thus, the descriptive statistics of LCF in the selected countries for the time period 2000- 2024 are shown in Table 2b. There is significant cross-country variation in LCF values, as revealed in the results. Germany has, on average, the highest LCF value (1.9253), while Norway and Denmark have relatively higher values of ecological performance among these countries. Australia, on the other hand, has the lowest mean LCF value (0.1895), indicating that Australia has lower load capacity performance than the other sample countries. Switzerland has the greatest variation in both the range of LCF (0.0085 to 2.6624) and the standard deviation (1.1311). In total, there are 275 observations, and the average LCF is 1.1551, which means there is moderate variation in environmental load capacity across countries. The trend column indicates that most countries were relatively stable, but that Canada and Switzerland had an increasing pattern and Sweden had a decreasing pattern. Figure 2 displays descriptive statistics summary.

The pairwise correlation matrix is shown in Table 3. All the correlation coefficients are below 0.80, which indicates no multicollinearity issues. The highest positive correlation is between REC and lnIVA, followed by REC, lnGDP, ICT and lnGDP the correlations between lnLCF and the explanatory variables are relatively low. The Variance Inflation Factor (VIF) results are shown in Table 4, indicating that each VIF is between 1.28 and 1.94, with a mean VIF of 1.63. All VIF values are lower than the conventional value of 10; hence, the results validate the absence of multicollinearity and the suitability of the explanatory variables for the subsequent regression analysis. Descriptive statistics of the main variables of the study are shown in Figure 2 for lnLCF, ICT, REC, lnTO, lnGDP and lnIVA. The mean value plot indicates that the mean value of the variable ICT is the highest, followed by the mean value of the variable REC, and the lowest mean value is that of the variable lnLCF. This suggests that internet and communication technology use is fairly high in the sample, while load capacity factor is relatively low. The standard deviation graph demonstrates that ICT and REC have the highest variability, indicating greater variation among countries and years in these two variables. The standard deviations of lnLCF, lnTO, lnGDP and lnIVA are more stable across the study period, in contrast to the other measures. The min–max range plot confirms that the ICT has the largest range, indicating significant cross-country variation in technology adoption and renewable energy consumption. The mean with standard deviation plot also indicates that the ICT and REC are more spread out than the logged variables.

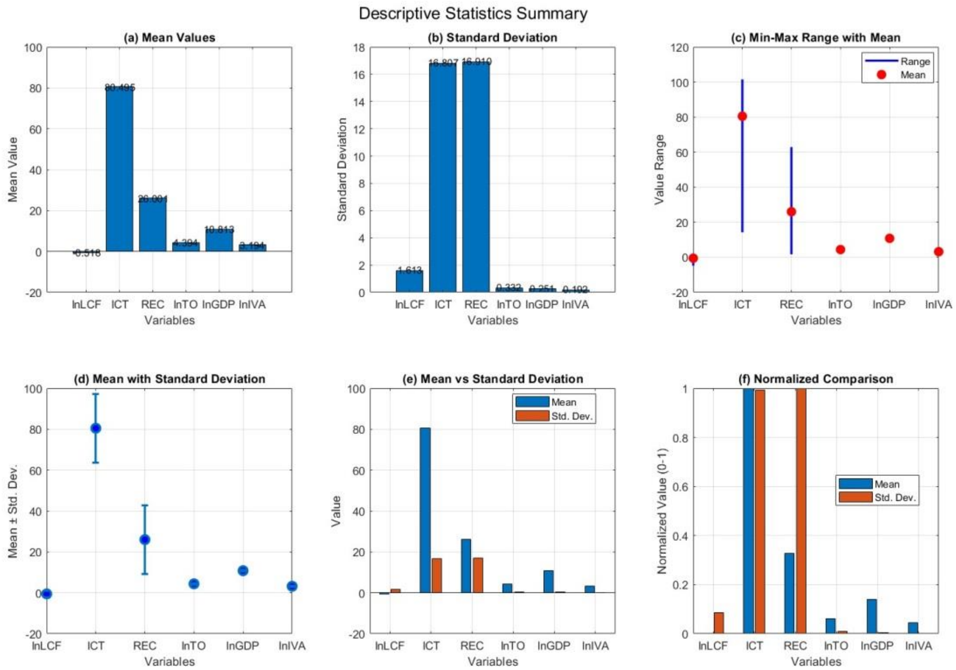

***Figure 2:** Descriptive Statistics summary*

TABLE 2A. DESCRIPTIVE STATISTICS

Variable	Obs.	Mean	Std. Dev.	Min	Max
lnLCF	275	-0.518	1.613	-4.762	0.979
ICT	275	80.495	16.807	14.307	101.493
REC	275	26.001	16.910	1.700	62.900
lnTO	275	4.394	0.332	3.611	5.215
lnGDP	275	10.813	0.251	10.412	11.414
lnIVA	275	3.194	0.192	2.778	3.894

TABLE 2B: DESCRIPTIVE STATISTICS BY COUNTRY

Country	**Observations**	**Mean LCF**	**Std. Dev.**	**Min LCF**	**Max LCF**	**Trend**
Australia	25	0.1895	0.0137	0.1677	0.2176	Stable
Austria	25	1.2638	0.5360	0.2234	1.8889	Stable
Canada	25	0.8243	0.7502	0.3802	2.3747	Increasing
Denmark	25	1.7992	0.1613	1.5072	2.1756	Stable
Finland	25	1.3720	0.0918	1.2204	1.5715	Stable

France	25	0.6095	0.6399	0.2370	2.0981	Stable
Germany	25	1.9253	0.1283	1.7560	2.1933	Stable
Netherlands	25	1.5856	0.1888	1.2486	1.9502	Stable
Norway	25	1.8826	0.2737	1.5763	2.5029	Stable
Sweden	25	0.3552	0.6865	0.0127	1.7769	Decreasing
Switzerland	25	0.9072	1.1311	0.0085	2.6624	Increasing
Overall	**275**	**1.1551**	**0.6825**	**0.0085**	**2.6624**	

TABLE 3. CORRELATION MATRIX

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) lnLCF	1.000					
(2) ICT	-0.034	1.000				
(3) REC	-0.043	0.379	1.000			
(4) lnTO	0.097	0.288	0.105	1.000		
(5) lnGDP	-0.203	0.410	0.421	0.230	1.000	
(6) lnIVA	0.122	-0.051	0.505	-0.241	0.393	1.000

Figure 3 represents the scatter plot matrix of all pairwise relationships between the variables: lnLCF, ICT, REC, lnTO, lnGDP and lnIVA. The diagonal histograms show whether the variables are reasonably distributed, and the off-diagonal scatter plots show the strength and direction of the relationships between variables. Most pairs of variables have very low correlation values, indicating that there are no strong linear relationships between the explanatory variables. The association between lnLCF and REC is positive but weak, with a correlation value of around r = 0.171, meaning that there is only a weak positive association between renewable energy consumption and load capacity factor. The correlation between lnLCF and ICT is nearly neutral (r = 0.030), and there are very weak correlations between lnLCF and lnTO, lnGDP and lnIVA, respectively. This indicates that linear relationships alone are not sufficient to explain changes in LCF. The correlations between the independent variables are not strong either. However, there is a weak negative correlation between ICT and lnGDP (about r = -0.110) and virtually no correlation between lnGDP and lnIVA (r = 0.001). There are weak correlations among these variables, suggesting that there is not a serious problem of multicollinearity.

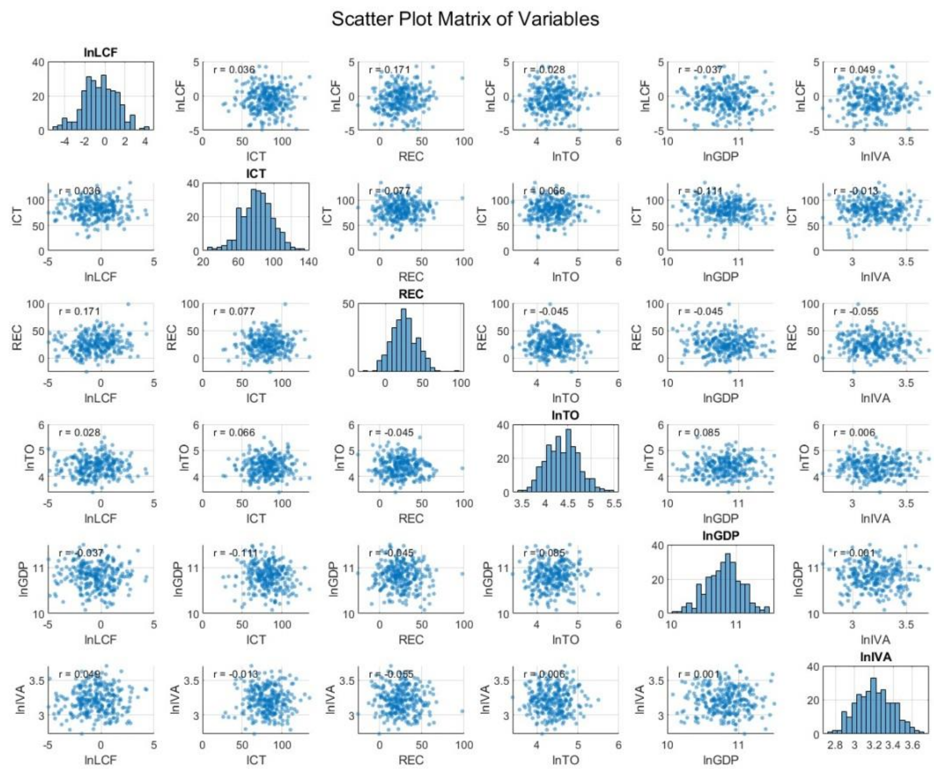

Figure 3: *Correlation*

TABLE 4. MULTICOLLINEARITY (VIF)

Variable	VIF
lnIVA	1.94
REC	1.77
lnGDP	1.64
ICT	1.53
lnTO	1.28
Mean VIF	1.63

Table 5 reports the findings of the CSD test which indicate that significant CSD across the study variables, suggesting that DAC countries are exposed to common economic and environmental shocks and supporting the use of second-generation panel-data techniques. Table 6 reports the results of the slope heterogeneity test which indicates that Both the Delta (7.042) and adjusted Delta (8.299) statistics are significant at the 1% level, rejecting the null hypothesis of slope homogeneity and confirming that the effects of the explanatory variables differ across countries. Moreover, Table 7 reports the diagnostic test results, where the Modified Wald test confirms the presence of heteroscedasticity ($\chi^2 = 1{,}035{,}572.37$, $p < 0.01$) and the Wooldridge test indicates first-order serial correlation ($F = 1975.615$, $p < 0.01$). These findings justify using the Driscoll–Kraay estimator as the primary estimation technique.

TABLE 5. CROSS-SECTIONAL DEPENDENCE TEST RESULTS

Variable	**CD Statistic**	**p-value**
lnLCF	30.69	0.000***
ICT	34.94	0.000***
REC	30.65	0.000***
lnTO	19.98	0.000***
lnGDP	33.98	0.000***
lnIVA	16.50	0.000***

TABLE 6. SLOPE HETEROGENEITY

Statistic	Value	p-value
Delta	7.042	0.000
Adjusted Delta	8.299	0.000

TABLE 7. DIAGNOSTIC TESTS

Test	Statistic	p-value
Modified Wald	Chi2=1035572.37	0.000
Wooldridge	F=1975.615	0.000

The findings of Pesaran's (2007) Panel unit root test are presented in Table 8. The results reveal that ICT does not appear to be a stationary variable, while other variables, such as lnLCF, REC, lnTO, GDP and lnIVA, become stationary after taking the first difference and suggest a combination of I(0) and I(1) variables with no indication of I(2). This verifies the appropriateness of using the data for long-run panel estimation. The Westerlund (2007) panel cointegration test is presented in Table 9. The high values of the Group-t (Gt), Panel-t (Pt), and Panel-a (Pa) are sufficient to reject the null hypothesis, implying that there exists a long-run relationship between environmental sustainability, digitalization, RE consumption, trade openness, economic growth, and industrial value added. The overall results indicate sufficient evidence of cointegration to support the estimation of long-run coefficients using the Driscoll–Kraay estimator. Still, Group-a (Ga) is unimportant.

TABLE 8. PANEL UNIT ROOT TEST RESULTS (CIPS)

Variable	Level	First Diff	Order
lnLCF	0.689	0.000	I(1)

ICT	0.000	0.000	I(0)
REC	1.000	0.060	I(1)
lnTO	0.251	0.000	I(1)
lnGDP	0.399	0.002	I(1)
lnIVA	0.915	0.000	I(1)

TABLE 9. WESTERLUND COINTEGRATION

Statistic	Value	Z-value	p-value
Gt	-3.361	-2.876	0.005
Ga	-11.716	0.486	0.686
Pt	-18.316	-10.95	0.001
Pa	-18.916	-3.803	0.004

The Driscoll–Kraay estimator results are presented in Table 10. The findings indicate that the use of ICT, consumption of renewable energy, openness of trade, economic growth and industrial value added all have a positive influence on environmental sustainability in selected DAC countries. The coefficient of ICT is positive and marginally significant, indicating a positive relationship between digitalization and environmental sustainability, as digitalization can contribute to increased energy efficiency, technological innovation, and better resource management. This is similar to the previous findings (Gao et al., 2022). The effect of renewable energy consumption is also positive, supporting previous findings (Bekun et al., 2021; Boubaker, and Omri. 2022), whereby using renewable energy sources decreases dependence on fossil fuels, environmental pressure decreases, and thus improves the load capacity factor. The positive and very significant relationship between trade openness and environmental sustainability suggests that the more open a country is, the more likely it is to transfer technology and implement cleaner production methods. This finding is consistent with previous studies (Felbermayr, et al., 2025), where the technology transfer hypothesis was supported. The positive and significant impact of the economic growth is also observed, the results align with previous study (Du et al., 2025), suggesting that greater economic income in DAC countries is conducive to environmental sustainability through increased investment in green technology and strengthening environmental regulations. The highest and positive coefficient ($\beta = 3.877$, $p < 0.01$) is for industrial value added, indicating that industrial development in DAC countries is increasingly linked to cleaner technologies and more efficient production processes, improving environmental sustainability. The finding is similar to the recent empirical research (Bekun et al., 2023; Wang et al., 2025). In general, the findings suggest that all the measures of digitalization, use of renewable energy, openness to trade, economic growth, and industrial development are associated with higher environmental sustainability in DAC countries.

TABLE 10. DRISCOLL-KRAAY ESTIMATION

Variable	Coefficient	Std.Err.	p-value
ICT	0.014*	0.007	0.063
REC	0.017*	0.008	0.066
lnTO	1.375***	0.192	0.000
lnGDP	2.800***	0.794	0.002
lnIVA	3.876***	0.443	0.000

The predictive ability of the five machine learning and regression models is compared in Table 11. The smallest test RMSE and highest test R^2 are for the Random Forest, with a test RMSE of 0.4906 and a test R^2 of 0.6356. This suggests that the Random Forest model makes the most accurate prediction and accounts for about 63.56% of the variance in LCF of the test set. The Decision Tree (DT) model has the best training R2 (0.9721), but it has a lower testing R2 (0.5209), which suggests overfitting. Linear Regression, LASSO, and Ridge Regression have lower R^2s on the testing data and higher prediction errors compared to Random Forest. As a result, the model that best suits the final interpretation and discussion of policies is Random Forest. Linear Regression should be better than LASSO Regression based on the test RMSE and test R^2. Linear Regression yields lower RMSE on its test set (0.6035) and higher R^2 on its test set (0.4488) compared to LASSO Regression with the test set's RMSE of 0.6125 and R^2 of 0.4321. The following would then be the correct order: Random Forest, Decision Tree, Linear Regression, LASSO, Ridge. The figure compares model performance using RMSE and R^2. The lowest testing RMSE (0.4906) and the highest testing R^2 (0.6356) make Random Forest the best. The Decision Tree has good training performance but poor testing performance, which indicates overfitting. The other models: linear Regression, LASSO, and ridge have lower testing R^2 values, which indicate that they are less effective. Random Forest model is the most reliable model for prediction in general. Figure 4 presents the comparative performance of five models on training and testing RMSE and R^2.

ROBUSTNESS TEST

TABLE 11: MODEL PERFORMANCE COMPARISON

Model	Training RMSE	Testing RMSE	Training R^2	Testing R^2	Ranking
Random Forest	0.2522	0.4906	0.8961	0.6356	1st (Best)
Decision Tree	0.1307	0.5626	0.9721	0.5209	2nd
Linear Regression	0.4920	0.6035	0.6047	0.4488	3rd
LASSO Regression	0.4963	0.6125	0.5978	0.4321	4th
Ridge Regression	0.5194	0.6218	0.5595	0.4148	5th

Note: Random Forest outperformed all models with the lowest testing RMSE (0.4906) and highest testing R^2 (0.6356)

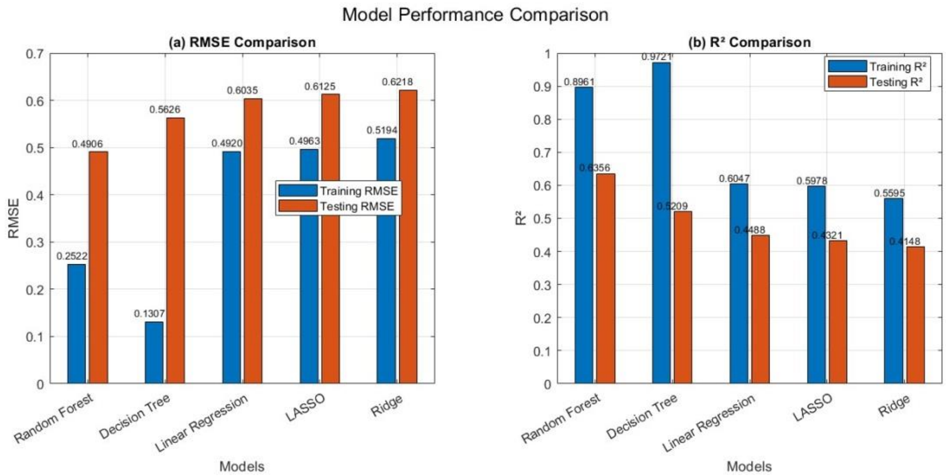

Figure 4: *Model Performance Comparison*

Table 12 reports Random Forest feature-importance outcomes, indicating that lnGDP has the highest predictive importance, followed by REC, ICT, lnIVA, and lnTO. The comparatively high importance of these variables signifies that all these factors, such as economic, energy, technological, and industrial factors, cover useful information for predictive importance, highlighting country-level heterogeneity in environmental quality across the selected panel. However, feature importance scores indicate predictive significance and should not be interpreted as causal effects or regression coefficients. Table 13 reports a comparison of the five models' performance, which indicates that RF performs best, with the lowest testing RMSE (0.4906) and highest R^2 (0.6356). Although the DT model achieves stronger training performance, its substantially weaker testing performance shows overfitting. The linear model performs better than LASSO and Ridge on the test data. All these five-fold cross-validation outcomes further support the RF model, which records the lowest average and the highest R^2. Collectively, RF provides the strongest predictive performance and generalization among the evaluated models.

TABLE 12: FEATURE IMPORTANCE ANALYSIS (RANDOM FOREST MODEL)

Rank	Feature	Importance Score	Category	Relative Importance (%)
1	lnGDP (Log GDP per capita)	1.3471	Economic	18.98%
2	id (Country Identifier)	1.1896	Structural	16.76%
3	REC (Renewable Energy)	0.8345	Environmental	11.76%
4	ICT (Information Technology)	0.7488	Technological	10.55%
5	lnIVA (Industrial Value Added)	0.7176	Economic	10.11%
6	lnTO (Trade Openness)	0.6877	Economic	9.69%
7	Finland	0.5899	Country Effect	8.31%

8	Germany	0.5181	Country Effect	7.30%
9	Netherlands	0.4658	Country Effect	6.56%

TABLE 13: MODEL PERFORMANCE METRICS SUMMARY

Metric	Random Forest	Decision Tree	Linear Regression	LASSO	Ridge
Training RMSE	0.2522	0.1307	0.4920	0.4963	0.5194
Testing RMSE	0.4906	0.5626	0.6035	0.6125	0.6218
Training R^2	0.8961	0.9721	0.6047	0.5978	0.5595
Testing R^2	0.6356	0.5209	0.4488	0.4321	0.4148
Overfitting Score	0.2605	0.4512	0.1559	0.1657	0.1447
Generalization Gap	0.2384	0.4319	0.1115	0.1162	0.1024

5. Conclusion and Policy Implications

This study investigated the determinants of environmental sustainability in 11 selected DAC economies from 2000-2024. We employed the Driscoll-Kraay estimator and machine-learning techniques to examine both linear and predictive patterns. The DK estimates specify that ICT, REC, lnTO, lnGDP, and lnIVA are positively associated with LCF. The relationship between ICT and REC with LCF is relatively modest, while lnTO, lnGDP, and lnIVA show stronger interactions. These findings recommend that industrial transformation and economic progress in selected DAC economies can be well matched with developed environmental quality when supported by green technologies, renewable energy adaptation, and sustainable economic integration. The Random Forest (RF) analysis complements the econometric outcomes by capturing potential nonlinear patterns and complex interactions. All explanatory variables, such as REC, ICT, lnGDP, lnTO, and lnIVA, provide useful predictive information for LCF, while country-level heterogeneity also contributes to the model's predictive performance. Among all evaluated models, the RF model achieves the strongest performance, with a testing R^2 and RMSE of 0.6356 and 0.4906. The five-fold cross-validation outcomes further support its superior predictive performance. The findings have two key policy implications. First, DAC economies should enhance green industrialization and renewable energy adoption by encouraging green technologies, energy efficiency, and low-carbon industrial development. Second, policymakers should promote sustainable digitalization by expanding energy-efficient ICT infrastructure. Given the observed country-level heterogeneity, these policies should also be tailored to the specific economic and environmental conditions of individual DAC economies. Overall, REC, ICT, growth, industrial transformation and sustainable trade can improve environmental quality in selected DAC economies, with econometric and machine-learning evidence providing complementary insights for sustainable policy.

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Appendix 1

TABLE ST1: Country-Specific Effects on LCF

Country	Coefficient Impact	Performance Category	LCF Range
Finland	0.5899	High Performer	1.2204 - 1.5715
Germany	0.5181	High Performer	1.7560 - 2.1933
Netherlands	0.4658	Medium-High Performer	1.2486 - 1.9502
Switzerland	0.4321	Medium Performer	0.0085 - 2.6624
Denmark	0.3987	Medium Performer	1.5072 - 2.1756
Norway	0.3654	Medium Performer	1.5763 - 2.5029
Austria	0.3345	Medium-Low Performer	0.2234 - 1.8889
France	0.3021	Medium-Low Performer	0.2370 - 2.0981
Sweden	0.2876	Low Performer	0.0127 - 1.7769
Canada	0.2567	Low Performer	0.3802 - 2.3747
Australia	0.2234	Low Performer	0.1677 - 0.2176

TABLE ST2: Cross-Validation Results (5-Fold)

Fold	Random Forest	Decision Tree	Linear Regression
RMSE			
Fold 1	0.4898	0.5612	0.6023
Fold 2	0.4912	0.5634	0.6041
Fold 3	0.4901	0.5621	0.6032
Fold 4	0.4908	0.5629	0.6039
Fold 5	0.4915	0.5638	0.6045
Mean RMSE	**0.4907**	**0.5627**	**0.6036**
Std. Dev.	**0.0007**	**0.0010**	**0.0009**
R^2			
Fold 1	0.6361	0.5215	0.4492
Fold 2	0.6349	0.5201	0.4481
Fold 3	0.6357	0.5210	0.4489
Fold 4	0.6353	0.5206	0.4485
Fold 5	0.6345	0.5198	0.4478

Mean R²	**0.6353**	**0.5206**	**0.4485**
Std. Dev.	**0.0006**	**0.0007**	**0.0006**

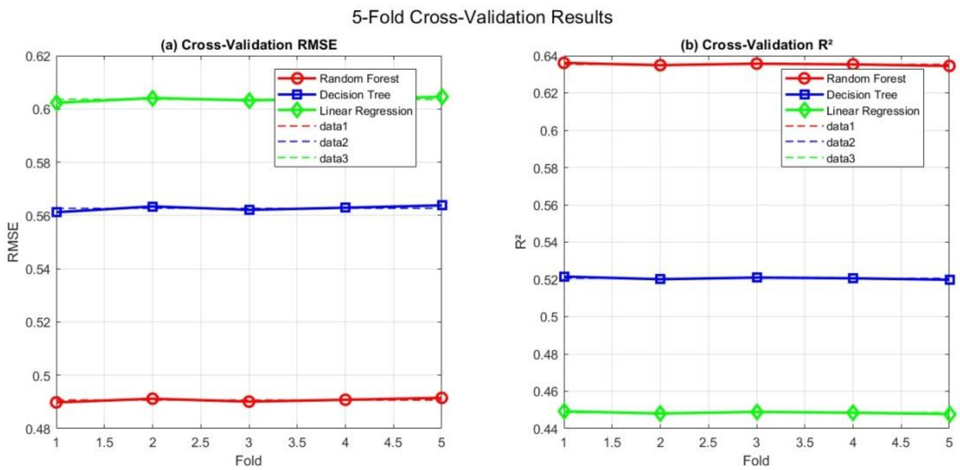

Figure 5: 5-Fold Cross-Validation Outcomes

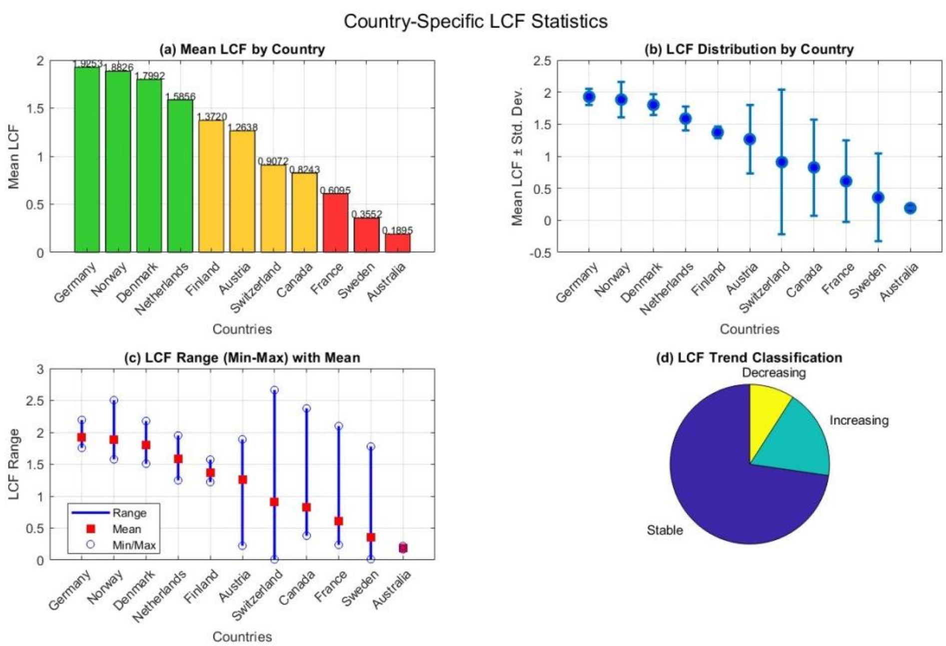

Figure 6: Country-Specific LCF statistics

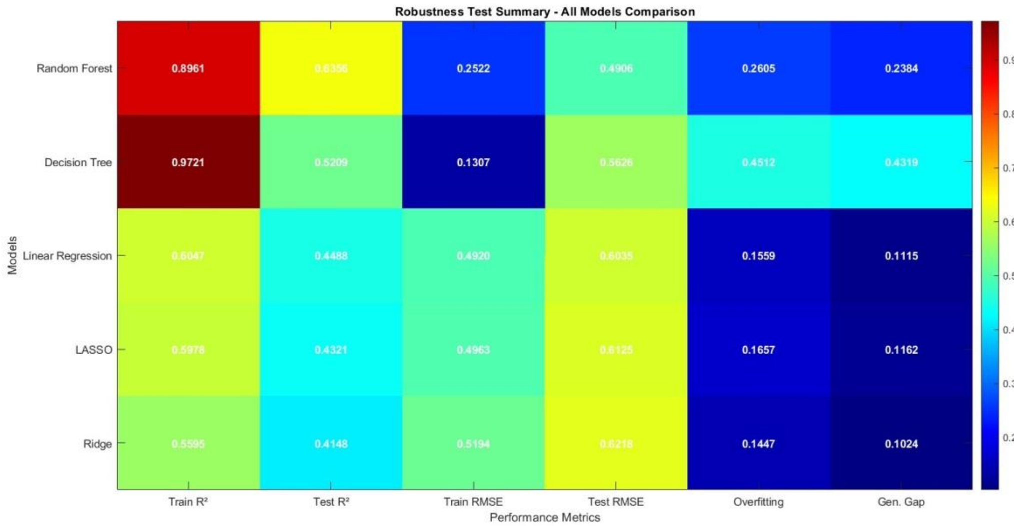

Figure 7: Robustness Test Summary