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Digital Transformation as a Driver of Green Growth: Empirical Evidence from OECD Countries, 2000-2022

Moussa Hezla
Department of Economics, College of Business and Economics, Ouargla University, El Oued, Algeria
E-mail: hezla.moussa@univ-ouargla.dz

Asmaa Zeggane
Department of Economics, College of Business and Economics, Mostaganem University, Mostaganem, Algeria
E-mail: asmaa.zeggane.az@gmail.com

Hadjer Khechekhouche
Department of Business Sciences, College of Business and Economics, Eloued University, El Oued, Algeria
E-mail: khechekhouche-hadjer@univ-eloued.dz

Abstract
This paper examines the multidimensional nexus between digital transformation and green growth across 35 Organisation for Economic Co-operation and Development (OECD) countries over 2000-2022.It focuses on whether digital infrastructure and e-government interact with renewable energy and environmental policy stringency to sustain productivity-enhancing, low-emission growth in advanced economies. Using harmonized OECD and UN sources, the study constructs a composite Digital Transformation Index via principal components analysis (PCA) and a production-frontier-consistent Green Growth Index. Second-generation panel estimators that address cross-sectional dependence, cointegration, and heterogeneity, alongside panel causality tests, are employed to identify long-run linkages and directionality. Findings indicate that digital transformation, environmental policy stringency, online public service quality, and renewable energy are positively associated with green growth, whereas public environmental Research and Development (R&D) shows no direct contemporaneous effect. Policy implications call for coordinated investment in digital infrastructure, innovation-friendly yet stringent environmental regulation, effective e-governance, and mechanisms that translate R&D into scalable deployment.

Keywords: Digital transformation, green growth, Principal components analysis, Renewable energy consumption, OECD countries

JEL classification: O33, Q56, C38, O44, C23

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1. Introduction

Digital transformation now shapes global economies in ways that go far beyond simple technological upgrades. What started as connectivity improvements has become something more fundamental structural shift that changes how we think about economic growth and environmental sustainability together. Climate pressures mount each year, and digital technologies offer tools to address them while maintaining economic progress. Recent research by Yi et al. (2024) suggests these technologies do not merely boost economic efficiency; they fundamentally alter the growth-environment relationship through better optimization, greater transparency, and innovation pathways.

Why does the digital-green relationship matter now? Advanced economies face a difficult balancing act. They must deliver productivity gains while meeting strict climate commitments under frameworks like the Paris Agreement and the European Green Deal, with most pledging net-zero emissions by 2050. This dual challenge makes the digital-green nexus a critical policy concern. Digital tools can help substantially: AI and the Internet of Things enable smarter energy management, digital twins improve building efficiency, and blockchain supports circular economy models and greener consumer choices. Virtual meetings cut travel emissions, while remote diagnostics reduce electronic waste. But digitalization itself creates pressures data centers consume vast energy, device manufacturing extracts resources, and electronic waste accumulates. Understanding whether digital transformation actually drives green productivity, through which channels, and under what conditions remains essential for coherent policy design that harnesses synergies while minimizing conflicts.

OECD countries provide an unusually good setting to examine these questions, for four reasons. First, these nations combine advanced digital infrastructure with mature environmental governance, which allows clearer observation of how technology and policy interact without the confounding effects of weak institutions found elsewhere. Member countries show high digitalization across domains e-commerce, telemedicine, digital public services alongside commitment to ambitious sustainability targets. Second, OECD members display rich policy variation: they have pioneered digital government while implementing diverse environmental regulations, renewable energy incentives, and R&D programs, which helps identify what works and where. Third, data quality and availability in OECD sources permit consistent measurement over long periods covering digitalization indicators, green productivity, renewable energy consumption, environmental R&D budgets, and policy stringency metrics, something rarely possible in broader samples. Fourth, lessons from OECD experiences carry global relevance, as emerging economies look to these countries for policy models, technology transfer mechanisms, and climate finance frameworks.

Recent empirical work confirms that digitalization influences green productivity in OECD nations through several channels: technological innovation, human capital upgrading, and industrial restructuring. Yet the picture is not straightforward. The effects appear nonlinear and seem to depend on threshold levels of innovation capacity and human capital. Some researchers worry that strict environmental rules might crowd out short-term growth, though the evidence here remains mixed. Moreover, translating public environmental R&D into tangible productivity gains depends heavily on diffusion mechanisms and institutional quality, raising questions about optimal policy combinations. Yi et al. (2024) show that while digitalization can increase resource trade flows, stringent environmental policies may temper this effect, reflecting inevitable trade-offs between market liberalization and environmental commitments. The benefits of digital transformation are

not automatically inclusive either. Rezgui and Bakari (2025) find that absent parallel investments in human capital health and education digitalization may widen social disparities rather than narrow them.

Despite growing scholarly attention, four critical gaps persist in understanding the digital-green relationship within OECD contexts. First, most studies target heterogeneous samples mixing advanced and emerging economies or focus on specific sectors construction (Shen and Wang, 2023), single countries (Febriyanti et al., 2024) which limits generalizability to advanced, digitally mature settings. Second, existing research often uses relatively narrow or outdated timeframes, such as 1990-2020 or 2010-2019, constraining the ability to capture recent technological advances, policy innovations, and post-pandemic digital acceleration. Third, many studies rely on first-generation panel estimators Autoregressive Distributed Lag (ARDL), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS) that may inadequately address cross-sectional dependence, slope heterogeneity, and mixed integration orders common in panel data, potentially yielding biased estimates. Fourth, prior research lacks integrated analysis of key transmission channels linking digital transformation to green growth, particularly how environmental policy stringency, online public service quality, renewable energy deployment, and environmental R&D effectiveness interact.

This study addresses these gaps by examining the digital transformation-green growth nexus across 35 OECD countries over 2000-2022. We make four contributions. First, we construct a composite Digital Transformation Index via Principal Components Analysis, aggregating mobile-cellular penetration, internet usage, and fixed-telephone subscriptions into a single measure of digital infrastructure breadth. Second, we develop a production-frontier-consistent Green Growth Index that measures efficient resource use labor and capital for GDP growth alongside substantial reductions in greenhouse gas emissions, reflecting progress toward sustainable growth through clean technology and effective environmental policies. Third, we employ advanced second-generation econometric techniques Cross-sectionally augmented Im, Pesaran and Shin (CIPS) and Cross-sectionally Augmented Dickey-Fuller (CADF) stationarity tests, Westerlund cointegration analysis, and the Augmented Mean Group (AMG) estimator explicitly designed to handle cross-sectional dependence, slope heterogeneity, and common dynamics in panel data. Fourth, we provide integrated analysis of five determinants: digital transformation, renewable energy consumption, government environmental R&D budget shares, environmental policy stringency, and the Online Service Index, alongside panel causality testing to uncover bidirectional linkages and feedback mechanisms.

How do our contributions differ from existing work? While most research examines heterogeneous samples mixing advanced and emerging economies (Rezgui and Bakari, 2025), single-country studies (Febriyanti et al., 2024), or specific sectors like construction (Shen and Wang, 2023) and manufacturing (Gao and Huang, 2024), we focus exclusively on 35 OECD countries a homogeneous group of advanced economies with mature digital infrastructure, strong environmental governance, and comparable institutions. This enables clearer identification of digital-green linkages unconfounded by severe capacity gaps or institutional weaknesses common in developing contexts, filling a void in the literature on advanced-economy sustainability transitions.

Whereas prior studies employ relatively narrow or outdated timeframes 1990-2020 (Caijuan et al., 2024), 2000-2019 (Borojo, 2024), or shorter panels our research covers 2000 to 2022, encompassing major policy milestones like Kyoto Protocol implementation, Paris Agreement adoption, and European Green Deal launch, plus technological breakthroughs including

smartphone diffusion, cloud computing, AI applications, and COVID-19 digital acceleration. This extended horizon permits robust long-run cointegration analysis and captures recent dynamics often absent in earlier studies.

Methodologically, many existing studies rely on first-generation panel estimators or standard fixed-effects models that assume cross-sectional independence an assumption frequently violated in internationally integrated economies. We deploy second-generation techniques explicitly designed to handle cross-sectional dependence, slope heterogeneity, and common factors: CIPS and CADF stationarity tests, Westerlund's (2007) cointegration analysis, and the AMG estimator. The AMG approach accounts for unobserved common factors and country-specific heterogeneity, providing more reliable coefficient estimates and avoiding bias from ignoring cross-country spillovers and global shocks. Additionally, panel causality testing via the Juodis, Karavias, and Sarafidis (JKS) method uncovers bidirectional linkages and feedback loops among variables, moving beyond simple correlation to establish causal directionality. While previous research examines isolated effects of digitalization (Yi et al., 2024; Li and Xu, 2024), renewable energy (Apergis and Payne, 2010), or environmental policies (Fatima et al., 2025), few studies integrate these drivers within a comprehensive framework. We construct composite indices and examine five theoretically motivated channels simultaneously: digital transformation, renewable energy consumption, government environmental R&D budget shares, environmental policy stringency, and online public service quality. This integrated approach reveals complex interactions, threshold effects, and policy complementarities invisible in single-channel analyses, offering a holistic view of dual-transition dynamics in advanced economies. Collectively, these contributions provide policy-relevant insights into how OECD countries can harness digital transformation to advance green growth, while identifying transmission mechanisms and bottlenecks such as the disconnect between environmental R&D spending and tangible productivity gains that require targeted interventions.

We test whether: (1) digital transformation exerts positive long-run effects on green productivity; (2) environmental policy stringency amplifies these effects in institutionally strong settings; (3) online public services enhance green growth through transparency, efficiency, and citizen engagement; (4) renewable energy consumption raises green productivity and energy security; and (5) public environmental R&D demonstrates direct effects or operates through indirect, lagged diffusion mechanisms.

The paper proceeds as follows. Section 2 reviews literature on digital transformation, renewable energy, environmental policies, and digital finance as green growth drivers, identifying convergences, divergences, and knowledge gaps. Section 3 details the empirical methodology: sample coverage, variable construction including PCA for the Digital Transformation Index and production-frontier modeling for the Green Growth Index econometric specification, and the sequential diagnostic testing framework covering cross-sectional dependence, slope heterogeneity, stationarity, cointegration, long-run estimation via AMG, and panel causality. Section 4 presents core empirical results and discusses their economic implications. Section 5 synthesizes main findings and formulates practical policy recommendations to enhance digital transformation's contribution to green growth within OECD countries, addressing challenges like digital divides, infrastructure investment needs, and ethical dimensions of digitalization beyond reductionist technical perspectives.

2. Literature review

Green growth constitutes a central pillar in contemporary economic and environmental scholarship. The literature converges on the view that it is the outcome of a complex interplay among several interrelated factors, including digital transformation as a driving force reshaping the growth-environment nexus; renewable energy consumption as a cornerstone of sustainability; research and development (R&D) and environmental policies as twin levers with dual impacts; and digital services and digital finance as contemporary channels for supporting innovation and enhancing transparency. Accordingly, the review of prior studies in this paper aims to survey the principal trends addressed within these strands of the literature, while highlighting points of convergence and divergence in their findings.

2.1. Digital transformation as a driving force for green growth

Researchers have found that digital transformation goes beyond improving economic efficiency it reshapes how growth and environmental quality relate to each other at a fundamental level. Yi et al. (2024) document this dual character: digitalization tends to raise resource trade flows, yet stringent environmental policies can dampen this effect, reflecting a trade-off between market liberalization and environmental commitments.

National experiences show this complexity. Febriyanti et al. (2024) found that digitalization in Indonesia improved efficiency and reduced carbon footprints, but success hinged on institutional quality and how widely firms adopted new technologies. At the sector level, Chinese construction firms used digital tools to boost green innovation and upgrade their workforce skills, though (Li et al., 2024) note the gains were larger in state-owned enterprises, which can afford longer-term investments.

Other research emphasizes complementarities. Chen et al. (2022) argue that information and communication technology cuts carbon emissions over time, but only when paired with policies that develop human capital. Demirel et al. (2022) make a similar point: environmental innovation alone produces limited effects unless combined with advanced digital technologies like artificial intelligence. Digitalization is not a one-dimensional tool.

Yet this generally positive picture becomes less clear when we look beyond advanced economies. Rezgui and Bakari (2025) offer a sobering perspective from Africa. While they confirm digitalization's positive economic and environmental impacts, they uncover a troubling gap: no significant causal link to "human development." This challenges the assumption that digitalization's benefits spread automatically through society. Without parallel investments in education and health, digital transformation may widen social disparities rather than narrow them an outcome that suggests growth can be non-inclusive.

External conditions matter as much as internal capabilities. Gao and Huang (2024) studied semiconductor firms and found that "supply chain integration" amplifies digitalization's positive effects, while "economic policy uncertainty" drags them down. Even digitally advanced firms depend on stable economic and regulatory environments. Kalwar (2024) supports this view, showing that the efficiency of logistics and information technology infrastructure forms prerequisites for green growth. The lesson: context shapes outcomes powerfully.

2.2. Renewable energy consumption as a pillar of green growth

Research consistently shows that renewable energy consumption forms a key pillar of green growth. Early work by Apergis and Payne (2010) and Žarković et al. (2022) demonstrated that clean energy investment enhances economic growth through job creation, innovation stimulus, and economic diversification that strengthens resilience against shocks. Regional assessments like (OECD, United Nations Development Programme, 2025) support these findings, confirming that transitioning to renewable sources reduces fossil fuel dependence and stabilizes energy costs, creating more sustainable economic conditions over time.

Eid et al. (2024) highlight an important distinction: renewable energy R&D proves far more effective at cutting emissions than fossil fuel research, underscoring the value of redirecting resources toward green fields. Yet the picture is not uniformly positive. Saqib et al. (2024) offer a more nuanced view, showing that environmental innovations and clean energy improve performance, but undirected financial expansion and continued heavy use of non-renewable energy can limit these gains a pattern reflecting complex interactions between technology and macroeconomic policies.

Geographic endowments matter considerably. Yuan et al. (2008) found that countries with abundant solar and wind resources achieve greater economic gains than less resource-rich nations, suggesting energy policies must account for domestic conditions. Policy frameworks appear crucial for successful transitions. Rennings (2000) showed that incentives and regulations can accelerate the shift and drive innovation toward sustainable pathways.

Recent work explores digital synergies. Gao and Huang (2024) show that the digital economy enhances renewable energy efficiency, particularly in cities using digital tools to cut waste and maximize output. Technological progress remains decisive European Commission report notes that clean energy innovation boosts countries' global competitiveness and creates employment. OECD (2015) found that renewable transitions bring direct environmental and health improvements, including lower health costs and higher productivity, which strengthen green growth's sustainability over the medium and long term.

2.3. Research and development and environmental policies as dual levers for green growth

Research suggests R&D and environmental policies form two fundamental pillars for green growth, though their effects prove complex and sometimes contradictory. On one side, education and R&D spending acts as a catalyst for environmental innovation. Huang et al. (2022) found that stronger human capital helps channel R&D expenditures into sustainable innovations. Borojo, (2024) showed R&D effectiveness doubles under financial openness, which facilitates capital flows and technology transfer. (Eid et al., 2024) reinforced this, finding renewable-energy R&D far more effective at cutting emissions than fossil fuel spending.

Yet the relationship is not straightforward. Arjomandi et al. (2023) revealed that while environmental spending boosts short-term growth, it may undermine long-term green productivity through "crowding-out" resources get diverted from other productive activities before green investments mature. The timing matters considerably.

Environmental policy stringency displays a similarly dual character. Fatima et al. (2025) and Maghyereh et al. (2025) confirm that stringent regulations boost green investments and can amplify

their positive effects, especially in economies with strong institutions like OECD countries. Anwar et al. (2025) found such policies mitigate negative effects of geopolitical risks on green growth. But the picture varies by context. Chen et al. (2022) showed excessive stringency may harm short-term economic growth, particularly in emerging economies. Akhtar et al. (2024) add a crucial dimension: the critical factor involves not just "policy design" but actual "implementation rigor" and governance quality shifting the challenge from legislation to practical enforcement.

R&D and environmental policies serve as strategic engines for green growth, but their impact hinges on two factors: how well economies balance environmental goals with short-term growth pressures, and how effectively governance systems translate expenditures and policies into tangible sustainable outcomes. The lesson appears clear spending and regulation alone do not guarantee results without strong institutions and careful calibration

2.4. The role of internet and digital finance in driving green growth

Recent work highlights how Internet and digital services reshape green growth trajectories at urban and community levels. Several studies (Wang et al., 2022; Huang et al., 2023) show that Internet diffusion enhances green productivity in Chinese cities through institutional innovation, with effects extending beyond local boundaries into neighboring regions via "spatial spillover effects." On the demand side, the Internet promotes greener consumption by raising awareness and cutting information costs, as Peng et al. (2023) confirm.

Digital finance provides another channel for improving green growth efficiency. Wu and Lin (2025) found that digital finance accelerates industrial transformation toward more sustainable pathways, though the impact is not linear it exhibits a "threshold effect" where positive outcomes become pronounced only once markets reach sufficient maturity and depth in digital and financial infrastructure. This suggests the Internet and digital finance are not merely support tools but structural drivers of green growth, provided institutional and digital environments exist to translate technological potential into tangible economic and environmental results.

3. Empirical methodology

The study covers 35 OECD countries over the period 2000-2022: Australia, Austria, Belgium, Canada, Colombia, Costa Rica, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States of America. These selected OECD economies are characterized by their advanced economic structures, high levels of digital infrastructure, and commitment to sustainability goals. This diverse yet integrated group offers a unique perspective on the evolving impacts of digitalization across different governmental and economic systems. Moreover, the availability of data and policy frameworks provides a solid foundation for econometric analysis, distinguishing these countries from others in exploring the relationship between digital transformation and green growth.

3.1. Study variables

The study incorporates as its dependent variable the Green Growth Index, and five explanatory variables: the Digital Transformation Index, Renewable Energy Consumption, the Government Environmental R&D Budget as a Share of Total Government R&D, Environmental Policy

Stringency, and the Online Service Index (Table 1). Accordingly, the econometric model is specified by the following equation:

$$GG_{it} = \alpha + \beta_1 DT_{it} + \beta_2 REN_{it} + \beta_3 RDENV_{it} + \beta_4 POL_{it} + \beta_5 OSI_{it} + \varepsilon_{it} \quad (1)$$

where:

- GG_{it} is the Green Growth Index for country i at time t;
- DT_{it} is the Digital Transformation Index;
- REN_{it} is Renewable Energy Consumption;
- $RDENV_{it}$ is the share of Government Environmental R&D Budget in total Government R&D;
- POL_{it} is Environmental Policy Stringency;
- OSI_{it} is the Online Service Index;
- α is the constant term;
- $\beta_1 - \beta_5$ are the coefficients to be estimated;
- ε_{it} is the error term.

Table 1 - Study variables and data sources

Code	Variable	Definition and unit of measurement	Source
GG	Green growth index	Efficient resources are used to raise GDP while reducing environmental impacts; measured using indicators that compare actual output with the maximum production frontier. Constructed (this study). Unit: index (dimensionless).	OECD Data Explorer; authors' construction
DT	Digital transformation	Composite index based on indicators such as mobile-cellular subscriptions, internet use, and fixed-telephone subscriptions; aggregated via Principal Component Analysis (PCA). Constructed (this study). Unit: index (dimensionless).	OECD Data authors' construction using (PCA) method
REN	Renewable energy consumption	Quantity of energy used from renewable sources (solar, wind, hydro, etc.) expressed as a share of total final energy consumption. Unit: percent (% of TFEC).	OECD Data Explorer
RDENV	Government environmental R&D budget	Share of government R&D appropriations/outlays specifically targeted to environmental objectives, expressed as a percentage of total government R&D budget. Unit: percent (%).	OECD Data Explorer
POL	Environmental policy stringency	Index capturing the level and stringency of government policies aimed at environmental protection. Unit: index (dimensionless).	OECD Data Explorer
OSI	Online Service Index	Index assessing the level and quality of online public services provided by government. Unit: index (dimensionless).	United Nations E-Government Knowledgebase

3.1.1. Green Growth Index

Green economic growth aims for the efficient utilization of available resources in the country (Kuzior, 2022) (labor and capital) for GDP growth and a substantial reduction in the environmental impact of production (Dźwigoł and Dźwigoł-Barosz, 2020). The efficiency of resource utilization in the country can be demonstrated through equation (2):

$$P^G = \left[\left(\frac{y,x,b}{x\ can\ produce(y,b)}\right)\right] \quad (2)$$

where are x the available resources in the country; y is the desirable output of production, b and is the undesirable output. This index allows for comparison of growth indicators across countries with maximum production frontiers, which represent the most efficient production.

The index measures changes in productivity over time by calculating the gap between actual output and maximum production level (Ojaleye and Narayanan, 2022). Changes in this gap over time reflect changes in the country's productivity and efficiency. Therefore, equation (2) can be represented as follows:

$$GG_t^{t+1} = \frac{1+\vec{D}_0^G(x^t,y^t,b^t;y^t,b^t)}{1+\vec{D}_0^G(x^{t+1},y^{t+1},b^{t+1};y^{t+1},b^{t+1})} \quad (3)$$

where GG_t^{t+1} is the green growth value for the country; x are the available resources in the country (labor force and gross capital formation); y is the desirable output (GDP for each country); b is the undesirable output (greenhouse gas emissions).

$$\vec{D}_0^G(x^s,y^s,b^s;y^s,b^s) = max\{\beta:(y^s+\beta y^s, b-\beta b^s \in P^G(x^s))\} \quad (4)$$

where $s = t; t+1$ is the global technology set.
The integration of environmental factors in equation (3) demonstrates the negative impact of production on the environment. The green growth index value ranges from 0 to infinity, where a value of 1 indicates no change in productivity over time, a value greater than 1 indicates an increase in productivity over time, and a value less than 1 indicates a decline in productivity over time. Using this index allows for the assessment of green growth as follows (Kwilinski et al., 2023):

- consideration of the qualitative and quantitative characteristics of input data, leading to a detailed estimation of production's environmental impact (Kwilinski et al., 2023b);
- comparison of productivity growth across countries, allowing identification of best practices on the path to green growth (Li et al., 2022).

3.1.2. Digital Transformation Index

Digital transformation contributes to connecting people and bridging distances, facilitating information exchange and fostering collaboration in innovative ways. It is a key driver of economic development by improving efficiency, enhancing innovation, and creating new employment opportunities. Consequently, governments and organizations pay close attention to it to ensure global competitiveness and improve public services. This includes investing in digital infrastructure, developing skills, and ensuring regulatory frameworks that balance innovation with privacy protection. To measure digital readiness (Rath et al., 2023), the Digital Transformation Index is constructed using Principal Components Analysis based on three variables: mobile phone

penetration, Internet usage, and fixed telephone subscriptions (Siddiqui and Singh, 2019), allowing comparison of countries' readiness and guiding policies toward optimal investment.

The Digital Transformation Index derived from these variables via PCA provides a composite score representing a country or region's digital readiness or level of digital infrastructure. The index helps compare digital transformation levels across different countries or regions, informing policymakers where digital infrastructure investments are needed.

3.1.3. Renewable energy consumption

Renewable energy consumption refers to the amount of energy produced from renewable natural sources such as solar, wind, and water, which differs from limited fossil fuels. This consumption serves as an important economic and environmental indicator, measured quantitatively in units such as terawatt-hours or as a percentage of total consumption (REN21, 2021). It impacts the economy by reducing fossil fuel imports and generating new industries and employment opportunities (IEA, 2020). Despite historically high costs, these have been reduced through technological advancement and economies of scale. Additionally, government policies and subsidies constitute a fundamental factor in supporting it, while its environmental benefits contribute to reducing emissions and promoting sustainability. Finally, renewable energy consumption enhances energy security by reducing dependence on fossil fuels and associated geopolitical risks (World Bank Group, 2021). Thus, it is considered an indicator of technological progress and countries' commitment to sustainable development.

3.1.4. Environmental Policy Stringency

The concept of environmental policy stringency refers to the degree of strictness of government policies aimed at environmental protection and encompasses several interconnected dimensions. Most prominently: regulatory intensity and scope, which determine the comprehensiveness and strictness of environmental regulations across multiple sectors, and economic impact, manifested in increased operational costs resulting from investment in clean technologies, while stimulating innovation and creating new markets. It also includes incentives and challenges such as taxes and subsidies to drive compliance, exemplified by carbon taxation. The effectiveness of these policies depends on their strict implementation, in addition to the necessity of dynamic adaptation to scientific and technological developments. Finally, achieving balance between environmental and economic objectives represents a central challenge in designing these policies (Mihai et al., 2023).

3.1.5. Government environmental research and development budget

The variable of government environmental research and development budget as a proportion of total government R&D represents a strategic indicator revealing the extent of government policy focus on environmental objectives within R&D spending. An increase in this ratio indicates enhanced environmental innovations, including the development of renewable energy technologies and waste management, while contributing to stimulating new sectors and creating employment opportunities that support sustainable economic growth. Additionally, this investment serves as a key measure of sustainable development, reflecting the government's commitment to environmental protection and achieving balance between innovation and economic growth (Tengfei and Ullah, 2024; Zhou et al., 2025).

3.1.6. Online Service Index

The Online Service Index refers to the quality and availability of digital government services as part of e-government efforts. The index encompasses key dimensions including availability and diversity of digital services such as taxation and business permits, accessibility and usability including multilingual support and user-friendly design, and service integration to enhance efficiency and reduce bureaucracy. The index also reflects transparency and citizen participation through data provision and interactive platforms, and economic impact manifested in improved efficiency, reduced costs, and enhanced business environment. Furthermore, it measures digital inclusion to ensure service accessibility for all groups and represents an indicator of the country's digital transformation level (United Nations Department of Economic and Social Affairs, 2022).

3.2. Model specification and empirical strategy

The empirical analysis follows a systematic econometric approach as illustrated in the methodological flowchart. The research methodology begins by examining the effects of digital transformation, renewable energy, environmental R&D, environmental policy stringency, and the Online Service Index on green growth. The analytical framework incorporates several sequential diagnostic tests to ensure robust estimation results. First, the Digital Transformation Index is constructed using Principal Components Analysis, followed by the Variance Inflation Factor test to assess multicollinearity among explanatory variables. Next, cross-sectional dependence is examined using the Pesaran (2004) CD test and the Pesaran (2015) CD test for weak cross-sectional dependence. The methodology then proceeds with a slope heterogeneity test, followed by stationarity analysis using the CIPS and CADF tests. Second-generation panel cointegration is assessed through the Westerlund (2007) test, leading to the estimation of long-run coefficients using the Augmented Mean Group estimator, which effectively addresses cross-sectional dependence and heterogeneity issues in panel data analysis.

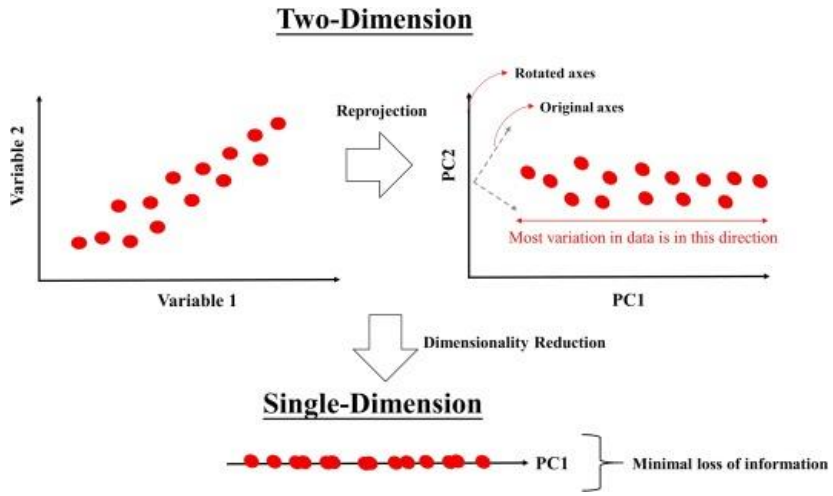
3.2.1. Principal Components Analysis (PCA)

Principal Components Analysis (PCA) is a technique used to capture variance and highlight strong patterns within a dataset. It is primarily employed to facilitate data exploration and visualization. PCA transforms the data into a new coordinate system such that the first principal component accounts for the greatest possible variance, and each subsequent component accounts for the highest possible variance under the constraint of being orthogonal to the preceding components. The resulting vectors form an uncorrelated orthogonal basis. PCA is sensitive to the relative scaling of the original variables (Jolliffe, 2005).

- Key features and uses of PCA: PCA is used to simplify data by reducing dimensionality while retaining the most significant variances, making analysis and interpretation easier. It also aids in visualizing complex data by projecting it into two- or three-dimensional spaces, enabling pattern and relationship recognition. Additionally, PCA helps reduce noise by preserving the most informative components and discarding less important ones, and it is used for feature extraction and data compression to generate new variables that are more efficient and less redundant than the original data (Abdi et al., 2013).

As illustrated in Figure 1, dimensionality reduction using Principal Components Analysis (PCA) demonstrates how original high-dimensional data can be effectively transformed and visualized in a lower-dimensional space.

Figure 1 - Dimensionality reduction using Principal Components Analysis (PCA)



Source: Bing shen How and Hon Loong Lam, "Sustainability Evaluation for Biomass Supply Chain Synthesis: Novel Principal Component Analysis (PCA) Aided Optimisation Approach," Journal of Cleaner Production 189 (July 10, 2018): 941-61, https://doi.org/10.1016/j.jclepro.2018.03.104.

Fundamental Equations of PCA: The mathematical foundation of PCA involves several steps and key equations.

- Standardization: Data is often standardized by subtracting the mean and scaling to unit variance before applying PCA, especially when variables are measured on different scales.

$$Z_j = \frac{x_j - \bar{x}}{\sigma} \quad (5)$$

where Z_j the standardized value of the variable, $\bar{x}$ the variable's arithmetic mean, and σ the variable's standard deviation.

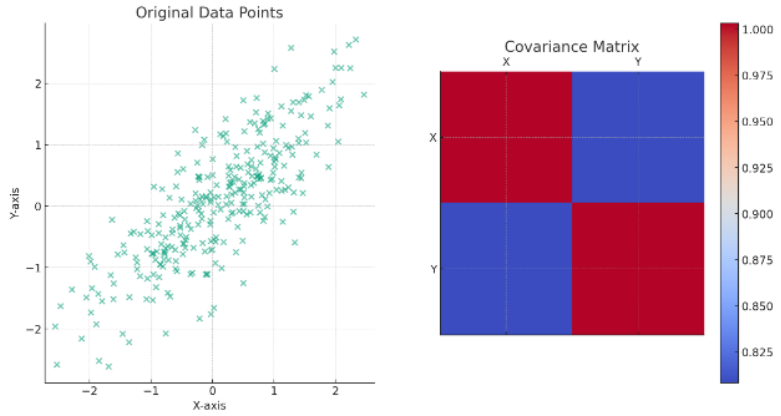
- Computation of the covariance matrix: PCA begins by computing the data's covariance matrix to understand how variables are related to one another.

$$\sum \quad = \frac{1}{n-1} XX' \quad (6)$$

- This equation shows how to compute the covariance matrix $\sum$ from the dataset matrix, where each column represents a variable and each row; XX' the covariance matrix is obtained as the product of X the matrix and its transpose X' (Wright et al., 2009).

As presented in Figure 2, the original data distribution and covariance matrix visualization illustrate how variables covariate one another and the structure of the data relationships. The heatmap representation in Figure 2 demonstrates the strength and direction of correlations between different variables in the dataset.

Figure 2 - Original data distribution and covariance matrix



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- Eigenvalue analysis: The covariance matrix is decomposed into its eigenvalues and eigenvectors. The eigenvectors indicate the directions of maximum variance (principal components), while the eigenvalues quantify the amount of variance along those directions.

$$\sum v = \lambda v \tag{7}$$

where: v denote the eigenvectors, and λ denote the eigenvalues.

- Selection of principal components: Principal components are chosen based on the eigenvalues. Eigenvectors associated with higher eigenvalues carry the greatest amount of information about the data distribution.

- Projection: The original data can be projected into the principal-component space using the selected eigenvectors to obtain principal component scores (Jolliffe and Cadima, 2016).

As illustrated in Figure 3, the projection of the original data using eigenvectors demonstrates how multidimensional data is transformed and visualized in a reduced-dimensional space, revealing the underlying structure and patterns in the dataset.

Figure 3 - Projection of the original data using eigenvectors

Source: Bing shen How and Hon Loong Lam, "Sustainability Evaluation for Biomass Supply Chain Synthesis: Novel Principal Component Analysis (PCA) Aided Optimisation Approach," Journal of Cleaner Production 189 (July 10, 2018): 941-61, https://doi.org/10.1016/j.jclepro.2018.03.104.

3.2.2. Cross-sectional independence test

Cross-sectional dependence in panel data represents a form of correlation arising from spatial effects, omitted common factors, social influences, and economic network interactions (Chudik and Pesaran, 2013). This leads to unreliable estimates because first-generation panel unit root and cointegration tests rely on the independence assumption, and its violation inflates the covariance matrix as the cross-sectional dimension expands. To detect this dependence, tests such as:

- CD test (Pesaran, 2004) for detecting strong cross-sectional dependence:

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=0}^{N} \sum_{j=i+1}^{N} T_{ij} \hat{p}_{ij}^2 \rightarrow N(0,1) \quad (8)$$

where ($\hat{p}_{ij}^2$) is the residual correlation coefficient between countries i and j, N is the number of countries, and T is the number of time periods. If the test rejects the null hypothesis of no cross-sectional dependence, it suggests that the countries under study are linked by common factors.

- CD test for weak cross-sectional dependence (Pesaran, 2015) is a second-generation test used to detect mild or weak dependence, where Pesaran Hashem confirmed that the issue of cross-sectional dependence tends to vanish as both T and N approach infinity, i.e., in very large samples.

3.2.3. Slope homogeneity test

Tests of slope homogeneity are fundamental in panel-data analysis, where the null hypothesis states that all coefficients are equal, while the alternative hypothesis posits that at least one differs. The Wald test is used for both small and large samples (Mutascu, 2016), whereas Swamy (1970) proposed a slope-homogeneity test under the assumption that N is relatively small compared with the time dimension T. Subsequently, Pesaran and Yamagata (2008) developed a test suitable for large panel data (Pesaran and Yamagata, 2008), which is computed as follows:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \quad (9)$$

where k is the number of regressors in the model, The properties of the small sample for testing $\tilde{\Delta}$ under normally distributed errors can be improved using the modified bias-corrected version, $\tilde{S}$ is the Swamy test statistic,

The small-sample properties of the test $\tilde{\Delta}$ under normally distributed errors can be improved using the following bias-adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right) \quad (10)$$

Where $\mathrm{E}(\tilde{\mathrm{z}}_{\mathrm{it}})$ mathematical expectation of the statistic $(\tilde{\mathrm{z}}_{\mathrm{it}})$

3.2.4. Panel unit root test

First-generation panel unit root tests do not account for cross-sectional dependence, leading to biased results (Hussain et al., 2020). We use so-called second-generation panel unit root tests, which are robust as they consider cross-sectional dependence. Specifically, we employ panel unit root tests CIPS and CADF to achieve consistent results (Pesaran, 2007). This test can provide reliable and consistent estimates in the presence of cross-sectional independence and/or slope heterogeneity. The test statistics are as follows:

$$CADF_i = t_i(N,T) = (y_i^T \bar{M} y_{i-1})^{-1}(y_{i-1}^T \bar{M} \triangle y_i) \Big/ \sqrt{\sigma_i^2 (y_i^T \bar{M} y_{i-1})^{-1}} \quad (11)$$

Where N is Number of cross-sectional units in the panel (e.g., countries or firms), and T is number of time periods per unit; these are the canonical panel dimensions in unit-root testing. y_i^T: Value of the variable under study for unit i at time ; $\Delta y_i^T = y_i^T - y_{i-1}^T$ denotes the first difference used in unit-root regressions. Pesaran developed the cross-sectionally augmented IPS (CIPS) test using CADF as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \quad (12)$$

3.2.5. Panel cointegration test

Since traditional panel cointegration tests do not account for cross-sectional dependence, Westerlund (2007) developed a cointegration test based on error correction that is robust even in the presence of cross-sectional dependence. This is generally known as the second-generation panel cointegration test. The core idea of the test is to examine the absence of cointegration by determining whether error correction is present among individual panel members or across the panel, as follows (Westerlund, 2007):

$$\Delta Y_{i,t} = \delta'_i d_t + \epsilon_i \left(Y_{i,t-1}\beta'_i X_{i,t-1}\right) + \sum_{j=1}^{p} \varphi_{i,j} Y_{i,j-1} + \sum_{j=0}^{p} \varphi_{i,j} Y_{i,j-1} + \mu_{i,t} \quad (13)$$

where ϵ_i is the coefficient representing the speed of adjustment toward equilibrium. Westerlund (2007) proposed four formulas including mean group and panel statistics, which are given in the following equations:

$$G_t = \frac{1}{N}\sum_{i=i}^{N} \frac{\epsilon_i}{Se(\hat{\epsilon}_i)} \quad (14)$$

$$G_a = \frac{1}{N}\sum_{i=i}^{N}\frac{T\epsilon_i}{\epsilon_i(1)} \quad (15)$$

$$P_t = \frac{\hat{\epsilon}_i}{NSe(\hat{\epsilon}_i)} \quad (16)$$

$$P_a = T\ \hat{\epsilon}_i \quad (17)$$

All statistics are calculated from least squares estimates, where *Gt* and *Ga* statistics are used to determine whether cointegration occurs in at least one cross-section, while *Pt* and *Pa* indicate whether common integration exists in the entire panel. To calculate cointegration, Westerlund (2007) generalized the testing procedures by employing a bootstrap approach.

3.2.6. Estimating the long-run model with the Augmented Mean Group (AMG)

The Augmented Mean Group (AMG) estimation method proposed by Eberhardt and Bond (2009) provides a common dynamic effect in panel data models to overcome the problem of cross-sectional dependence. AMG matches Common Correlated Effects Mean Group (CCEMG) in addressing panel data issues in a similar manner; however, the main difference between the two methods lies in the estimation process for unobserved variables, which are considered a nuisance in CCEMG but a common dynamic mechanism in AMG.

The AMG estimator performs a two-step process to assess the common dynamic effects of unobserved variables. In the first step, time dummy variables are introduced into the pooled OLS regression, resulting in a common dynamic effect. In the second step, the AMG estimator is obtained from the mean regression parameters for each previously created group regression. The two steps of AMG can be expressed as follows:

Step one:

$$\Delta y_{it} = \alpha_i + \beta_i \Delta x_{it} + \gamma_i f_t + \sum_{t=2}^{T} \delta_t \Delta D_t + \varepsilon_{it} \quad (18)$$

Step two:

$$\hat{\beta}AMG = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i \quad (19)$$

Where Δ denotes the first difference, D_t and δ_t represent the time dummies and coefficients of time dummies, respectively, which define the common dynamic process. $\hat{\beta}_i$ Denotes the estimator coefficients β_i, and $\hat{\beta}AMG$ is the Augmented Mean Group estimator average.

3.2.7. Panel Granger Causality Testing (JKS approach)

The Granger causality concept, first introduced by Granger (Granger, 1969), provides a statistical framework for assessing predictive relationships between variables in time-series. According to this approach, a variable X is said to be "Granger-cause" variable Y if past values of X contain information that helps predict Y, after controlling for other variables in the model. Although the term "Granger causality" implies a predictive relationship rather than true causation, it has become standard terminology in applied econometrics (Müller et al., 2019).

Granger causality has been widely applied across various disciplines, including economics, engineering, and health sciences. In panel data settings, the concept has been extended to allow

testing across multiple cross-sectional units and time periods. Several methods have emerged to address the complexities of such data, including those by Holtz-Eakin et al. (1988), Dumitrescu and Hurlin (2012), Emirmahmutoglu and Kose (2011), and, more recently, Juodis et al. (2021).

This study adopts the Juodis-Karavias-Sarafidis (JKS) test, which is an advanced panel Granger non-causality test designed for large panels with fixed effects and lagged dependent variables. It corrects for the Nickell bias using a Half-Panel Jackknife (HPJ) estimator, making it robust to cross-sectional dependence and slope heterogeneity, and suitable for detecting causal relationships in dynamic panel data.

The model is specified as:

$$y_{i,t} = \phi_{0,i} + \sum_{p=1}^{P} \phi_{p,i} y_{i,t} + \sum_{p=1}^{P} \beta_{p,i} x_{i,t-p} + \tau_{i,t} \quad (20)$$

where:

- $\phi_{0,i}$ is an individual-specific intercept;
- $\phi_{p,i}$ and $\beta_{p,i}$ are the lag coefficients for *y* and *x*, respectively;
- $\tau_{i,t}$ is the error term;
- $x_{i,t-p}$ is scalar, and lag lengths are identical for *y* and *x*.

The null hypothesis of non-causality is expressed as:

$$H_0: \beta_{p,i} = 0 \ \forall i, p \quad (21)$$

The test employs the Half-Panel Jackknife (HPJ) bias correction to produce consistent estimates in panels with large cross-sectional (N) and time-series (T) dimensions. The JKS method offers several key advantages: it is robust to cross-sectional dependence and slope heterogeneity, demonstrates superior size and power properties, performs well in large panels, and effectively addresses issues related to omitted variable bias.

4. Empirical results

In this section, we present the empirical results of the analysis of the impact of digitalization on green growth - for 35 countries from the Organization for Economic Co-operation and Development (OECD) for the period from 2000 to 2022. We explore in depth the causal relationship between five key variables: digital transformation, renewable energy, environmental R&D, environmental policy stringency, and the Online Service Index.

4.1. Results of Principal Components Analysis (PCA)

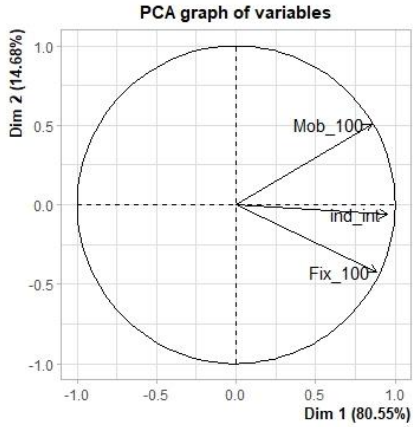
The following Table 2 summarizes the results of the Principal Components Analysis (PCA) for the three studied variables: mobile phone penetration (Mob_100), internet usage index (Ind_int), and number of fixed telephone subscriptions (Fix_100). The table includes the correlation values with the components, coordinates of the principal components, the contribution percentage of each variable to each component, the relative priority of each variable, as well as indicator values such as eigenvalues and the explained and cumulative variance percentages of these components. This analysis reflects the influence and representation of these variables in the main dimensions and their explanation of variance in the data.

Table 2 - PCA-based optimization for Digital Transformation Index

Variables	Correlation (Mob_100/Ind_ int/Fix_100)	Coordinates (Comp1/Comp2/ Comp3)	Contribution (%) (Comp1/Comp2/ Comp3)	Priority %	Score (PC1 / PC2 / PC3)
Mob_100	+/+/+	0.852 / 0.508 / 0.128	30.04 / 58.53 / 11.43	40%	0.29 / 0.08 / 0.03
Ind_int	+/+/+	0.953 / -0.061 / -0.297	37.58 / 0.85 / 61.57	35%	0.30 / 0.04 / 0.01
Fix_100	+/+/+	0.885 / -0.423 / 0.197	32.38 / 40.61 / 27.00	25%	0.21 / 0.03 / 0.005
Net Score	-	-	≈ 80% (Comp1) + 15% (Comp2) ≈ 95%	-	-
Eigenvalue	-	-	2.4163 / 0.4403 / 0.1433	-	-
Explained Variance %	-	-	80.55 / 14.68 / 4.77	-	-
Cumulative Variance %	-	-	80.55 / 95.22 / 100	-	-

Correlation matrix analysis (Table 2) highlights strong positive relationships among digital transformation variables (mobile phone subscriptions, internet usage, and fixed phone subscriptions), with the strongest correlation observed between internet usage and fixed phone subscriptions (0.8907), reflecting the robustness of the telecommunications infrastructure. Principal Components Analysis (Table 6) shows that the first component explains approximately 80.55% of the variance, while the second component contributes 14.68%, bringing the cumulative variance to 95.22%, supporting the retention of both components together to construct the digital transformation index. As presented in Figure 4, variable coordinates and component representation percentages demonstrate the relative contributions of each digital transformation variable to the principal components. Variable coordinates indicate high loadings on the first component for all variables (mobile subscriptions: 0.852, internet usage: 0.953, fixed phone: 0.885), representing a general dimension of "digital connectivity and access," whereas the second and third components account for lesser influential aspects. Variable contributions reveal internet usage as the dominant influence in the first component, with mobile phones playing a key role in the second, and fixed phones having a balanced influence across both dimensions. Consequently, the final digital transformation index primarily reflects the first component with relative support from the second, retaining about 95% of the total information, consistent with Kaiser criterion and cumulative variance standards (Qu, 2007; Izenman, 2008; Jolliffe and Cadima, 2016).

Figure 4 - Variable coordinates and component representation percentages



Source: authors' owns calculation using Stata statistical software.

4.2. Descriptive statistics

Table 3 presents the descriptive statistics for the main variables used in the study, including the number of observations (Obs), the arithmetic mean (Mean), the standard deviation (Std. dev.), the minimum (Min), and the maximum (Max) for each variable. These figures provide a comprehensive overview of the data's characteristics and distribution over the study period.

Table 3 - Descriptive statistics Results

Variable	Obs.	Mean	Std. Dev.	Min	Max
GG	805	1.179228	1.936312	0	35.04408
DT	805	5.42E-13	1.556477	-3.97152	2.185923
RDENV	805	3.183881	3.502386	0.05	42
POL	805	2.61973	0.9168384	0.3055556	4.888889
OSI	805	0.679863	0.2092496	-0.0142247	1.001595
REN	805	18.21614	13.53912	0.69	61.29

The green growth index reflects countries' commitment to environmental sustainability, with a mean of 1.18 and notable dispersion; Estonia recorded the lowest value (0.11) versus the highest for Switzerland (7.05), indicating disparities in green policies. As for digital transformation, values ranged between -3.97 (Colombia) and 2.19 (Estonia), reflecting differences in the levels of adoption of digital technologies. Renewable energy consumption averaged 18.2% of total final energy consumption, with a sharp disparity between South Korea (0.69%) and Norway (61.29%). Environmental policy stringency showed an average of 2.6, with New Zealand at the lowest level (0.31) and France at the highest (4.89). For the online service index, the mean was 0.68, with challenges in countries such as South Korea (-0.014) and advancement in the United States (1.002). Finally, analysis of the environmental R&D budget showed an average of 3.18% of total government R&D, with large variation between Lithuania (0.05%) and Colombia (42%), reflecting differing priorities for environmental investment across countries.

4.3. Correlation matrix

Table 4 presents the correlation matrix that shows the strength and direction of the pairwise relationships among the study indicators: green growth (GG), digital transformation (DT), environmental R&D (RDENV), environmental policy stringency (POL), online government services (OSI), and renewable energy (REN). These values help form an initial understanding of the degree of concordance or divergence between the variables before moving to causal analysis or model building.

Table 4 - Correlation Matrix Results

	GG	DT	RDENV	POL	OSI	REN
GG	1					
DT	0.5941	1				
RDENV	-0.2694	-0.0372	1			
POL	0.6197	0.6902	-0.2472	1		
OSI	0.3205	0.6486	-0.0515	0.2757	1	
REN	0.497	0.4046	0.0504	0.2683	0.3337	1

The correlation matrix analysis reveals significant relationships between several variables and green growth. There is a strong positive relationship between digital transformation and green growth, meaning that countries that rely more heavily on digital technologies achieve better progress in environmental sustainability. On the other hand, a negative relationship is observed between green growth and environmental research and development, indicating that countries investing in this area may not see immediate results in terms of green growth, perhaps because such investments require time to yield tangible effects. Likewise, there is a strong positive relationship between environmental policy stringency and green growth, indicating that countries that adopt strict environmental policies achieve better sustainability performance. In addition, the analysis shows that robust electronic service infrastructure contributes moderately to improving green growth, while renewable energy consumption plays a major role in achieving positive outcomes on this indicator, as reliance on clean energy sources is closely associated with achieving sustainable growth.

4.4. Cross-sectional dependence analysis

Table 5 summarizes Pesaran's cross-sectional dependence diagnostics CD (2004) for strong dependence and CD for weak dependence (2015). across the variables. P-values below the 5% threshold warrant rejection of the null of cross-sectional independence at conventional significance levels, indicating statistically significant dependence and motivating the application of second-generation panel tests and estimators in subsequent analysis.

Table 5 - Cross-sectional dependence results

Variables	Pesaran (2004) CD test		Pesaran (2015) CD test for weak cross-sectional dependence	
	P-Value	Statistic	P-Value	CSD
GG	0.000	80.91	0.000	80.91
DT	0.000	111.56	0.000	111.56
RDENV	0.000	-0.50	0.000	24.03
POL	0.000	79.79	0.000	79.19
OSI	0.000	74.37	0.000	74.37
REN	0.000	70.20	0.000	73.47

The results of the cross-sectional independence diagnostics indicate rejection of the null hypothesis of cross-sectional independence at the 1% significance level across the applied tests. Given that cross-sectional dependence implies shocks in any one country in the study sample can be readily transmitted to other countries, the commonly used first-generation panel models are therefore unsuitable for this study.

4.5. Homogeneity analysis

Table 6 reports the results of the slope homogeneity test, presenting the Delta statistic and its adjusted counterpart. These diagnostics evaluate the null hypothesis that slope coefficients are homogeneous across cross-sectional units and detect potential heterogeneity. The reported values enable assessment of statistical significance and inform the selection of appropriate panel estimation strategies in subsequent analysis.

Table 6 - Heterogeneity test results

Tests	Delta	P-Value
$\tilde{\Delta}$	4.812	0.000
adj $\tilde{\Delta}$	5.893	0.000

Table 6 reports the results of the slope homogeneity test. Based on the outcomes of both test statistics, the null hypothesis of homogeneous slopes is rejected at the 1% significance level; accordingly, panel-data methods that account for both cross-sectional dependence and slope heterogeneity should be employed.

4.6. Stationarity analysis

Table 7 reports the results of second-generation panel unit root tests using the CIPS and CADF procedures, evaluated at both levels and first differences for the study variables. These results assess stationarity and identify the order of integration for each series, thereby informing subsequent cointegration testing and the choice of an appropriate estimation strategy; asterisks denote conventional significance levels for the reported test statistics.

Table 7 - Stationarity analysis results

Variables	CIPS				CADF			
	Levels		1st Difference		Levels		1st Difference	
	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend
GG	-2.876***	-3.056***	-4.280***	-4.302***	-2.098**	-2.316	-3.201***	-3.140***
DT	-1.750	-2.527	-4.315***	-4.498***	-1.896	-2.504	-3.030***	-3.132***
RDENV	-1.748	-2.319	-4.431***	-4.573***	-1.588	-2.136	-3.284***	-3.359***
POL	-2.577***	-2.854***	-4.516***	-4.480***	-2.553***	-2.883***	-3.475***	-3.315***
OSI	-3.467***	-3.714***	-5.933***	-6.038***	-2.290***	-2.612**	-4.214***	-4.104***
REN	-1.990	-2.216	-4.449***	-4.596***	-1.816	-1.925	-3.040***	-3.509***

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

The results in Table 7 indicate that, according to the CIPS test, the green growth index, environmental policy stringency, and online service index are stationary at levels, whereas the remaining variables namely, the digital transformation index, renewable energy consumption, and government environmental R&D budget achieve stationarity after first differencing. In contrast, the CADF test shows that environmental policy stringency and the online service index are stationary at levels, with the other variables becoming stationary after first differencing. Consequently, the null hypothesis of a unit root is rejected in favor of the alternative hypothesis that the variables are stationary at first differences.

4.7. Second-generation panel cointegration test

Table 8 presents the results of the Westerlund (2007) panel cointegration test, reporting the Gt, Ga, Pt, and Pa statistics alongside their Z-values, conventional p-values, and robust p-values. These diagnostics evaluate the existence of a long run cointegrating relationship among the variables under cross-sectional dependence, thereby guiding the selection of suitable second-generation panel estimators for subsequent analysis.

Table 8 - Second-generation panel cointegration test results

Statistic	Value	Z-value	P-value	Robust P-value
Gt	-2.454	-1.39	0.081	0.051
Ga	-5.098	4.805	1.000	0.001
Pt	-1.525	7.324	1.000	0.994
Pa	-18.769	-7.51	0.000	0.000

To assess the presence of cointegration, the Westerlund (2007) test extends the testing procedure by employing bootstrap resampling to address cross-sectional dependence and heterogeneity, thereby enhancing the robustness of statistical inference in panel data. The results reported above display a clear pattern, the Gt statistics reject the null in favor of the alternative at the 5% significance level, indicating the existence of cointegration, while the Pt and Pa statistics provide even stronger support at the 1% level. Accordingly, there is clear evidence of a long-run relationship between the dependent variable and the explanatory variables in the model, which justifies proceeding to estimate long-run coefficients within second-generation frameworks.

4.8. Estimation using the Augmented Mean Group (AMG) estimator

Given that the cointegration tests confirm the existence of a long-run relationship between the green growth index and the set of explanatory variables, we employ the Augmented Mean Group (AMG) estimator to estimate dynamic long-run coefficients while allowing for cross-sectional heterogeneity and accounting for unobserved common factors. The AMG methodology proceeds by extracting a panel-wide common dynamic effect through estimating a first-difference model with time dummies and then incorporating this effect into unit-specific regressions to obtain unit-level long-run parameters, which are subsequently aggregated by averaging across units. This approach accommodates cross-sectional dependence, heterogeneity in slopes and intercepts, and potential nonstationarity in the series, thereby enhancing the consistency of the estimates in the presence of macroeconomic shocks or unobserved influences. Accordingly, we estimate the long-run effects of green growth with respect to the relevant regressors using AMG, compute robust standard errors that account for heteroskedasticity and within-unit serial correlation, and conduct subsequent robustness checks to assess the stability of the results across specifications and units (Table 9).

Table 9 - Augmented Mean Group (AMG) estimator results

Variables	Coefficient	p-value
DT	0.0267	0.002
RDENV	-0.0011	0.787
POL	0.0353	0.022
OSI	0.0859	0.056
REN	0.0099	0.000
Wald test	37.58	0.000
CD	-0.02	0.984

Long-run estimation results indicate statistically significant positive relationships between the green growth index and several key explanatory variables. Specifically, a one-unit increase in the digital transformation index raises the green growth index by 0.0267 units; environmental policy stringency also has a positive effect, with a one-unit increase lifting the index by 0.0353 units. Likewise, the online service index materially promotes green growth, as each one-unit increase elevates the index by 0.0859 units. Renewable energy consumption exerts a statistically significant positive impact as well, whereby a one-unit increase augments the green growth index by 0.0099 units. By contrast, government environmental R&D expenditures do not exhibit a statistically significant effect on green growth. Finally, the Pesaran CD test indicates that the estimated model does not suffer from cross-sectional dependence, which strengthens the credibility of the results.

4.9. Dynamic causal analysis

Table 10 presents the results of the Granger non-causality tests, where the null hypothesis H_0 states that variable X does not Granger-cause Y. The reported values are p-values; rejection of the null occurs at the 5% significance level (i.e., $p \leq 0.05$), indicating the presence of Granger causality from X to Y.

Table 10 - Panel Granger non-causality test results (p-values) results

Null Hypothesis	WALL-Stat	Z-Stat	P-value	Decision
DT ≠ > GG	22.5451	4.75	0.0000	DT ⇔ GG
GG ≠ > DT	19.0749	4.37	0.0000	
REN ≠ > GG	14.3751	3.79	0.0001	REN ⇔ GG
GG ≠ > REN	5.6928	-2.39	0.0170	
REN ≠ > DT	43.9155	-6.63	0.0000	REN ⇔ DT
DT ≠ > REN	10.7323	3.28	0.0011	
POL ≠ > GG	80.8510	8.99	0.0000	POL ⇒ GG
GG ≠ > POL	2.8767	-1.70	0.0899	
REN ≠ > POL	11.8627	-3.44	0.0006	REN ⇔ POL
POL ≠ > REN	28.1134	5.30	0.0000	
DT ≠ > POL	19.8813	4.46	0.0000	DT ⇔ POL
POL ≠ > DT	11.6704	-3.42	0.0006	
OSI ≠ > GG	12.8864	3.59	0.0003	OSI ⇒ GG
GG ≠ > OSI	0.3472	-0.59	0.5557	
REN ≠ > OSI	69.4776	8.34	0.0000	REN ⇔ OSI
OSI ≠ > REN	17.8291	4.22	0.0000	
DT ≠ > OSI	6.1779	2.49	0.0129	DT ⇔ OSI
OSI ≠ > DT	20.5928	-4.54	0.0000	
RDENV ≠ > GG	0.0000	0.00	0.9983	GG ⇒ RDENV
GG ≠ > RDENV	7.3249	2.71	0.0068	
REN ≠ > RDENV	0.6199	-0.79	0.4311	REN ⇏ RDENV
RDENV ≠ > REN	0.8191	0.91	0.3654	
RDENV ≠ > DT	11.2141	3.35	0.0008	RDENV ⇒ DT
DT ≠ > RDENV	2.3063	-1.52	0.1289	
POL ≠ > RDENV	2.1762	1.48	0.1402	POL ⇏ RDENV
RDENV ≠ > POL	0.3322	0.58	0.5644	
OSI ≠ > RDENV	2.2437	0.57	0.5657	OSI ⇏ RDENV
RDENV ≠ > OSI	1.3298	-1.15	0.2488	

Note: the null hypothesis is rejected at the 5% significance level if the p-value is less than or equal to 0.05. Bold values indicate significant causal links.

The results of the JKS panel Granger non-causality test, presented in Table 10, indicate the presence of a strong causal between green growth (GG) and the other variables, with most p-values below 0.05, which implies rejecting the null hypotheses of non-causality in most cases at conventional significance levels such as 5% and 1%. There is bidirectional causality between GG and digital transformation (DT), and between GG and renewable energy (REN), where the Wald and Z statistics are large in both directions, suggesting that digital development and the adoption

of renewable energy both promote green growth, while at the same time each of them is reinforced by improvements in green growth. There is also strong causal interaction between GG and the stringency of environmental policies (POL), and between GG and the online service or digital infrastructure index (OSI), indicating that stricter policies and improved digital openness/services are temporally associated with better green growth indicators.

The results also show a dense causal among DT, REN, POL, and OSI: there is almost bidirectional causality between DT and REN, between DT and POL, and between DT and OSI, in addition to strong mutual relationships between REN and POL and between REN and OSI. This means that digital transformation, renewable energy, environmental policies, and digital openness/services form an interconnected system that dynamically reinforces itself over time. In contrast, the variable of environmental R&D expenditure (RDENV) does not exhibit a statistically significant effect on GG, REN, POL, or OSI (with p-values greater than 0.05), while there is only causality from GG to RDENV and from RDENV to DT. This implies that improvements in green growth subsequently lead to higher environmental spending, and that this spending is associated with the evolution of digital transformation, but it has not yet translated into a direct measurable impact on the other variables, which may indicate time lags between investment in environmental R&D and its materialization into outcomes for green growth and renewable energy consumption.

5. Economic interpretations of the results

Green growth in OECD countries does not emerge from isolated policy interventions but rather from the interaction of multiple, mutually reinforcing mechanisms. The empirical results reveal that digital transformation, renewable energy deployment, environmental regulation, and e-governance platforms operate as interdependent drivers that shape sustainable economic trajectories through complex feedback loops.

Digital technologies serve as foundational infrastructure for sustainable growth, with the analysis confirming bidirectional causal relationships between digital transformation (DT) and both renewable energy consumption (REN) and environmental policy stringency (POL). This two-way influence demonstrates that digitalization not only enhances productivity and energy efficiency through optimized resource allocation and real-time monitoring systems but also creates enabling conditions for stricter environmental regulation by improving firms' capacity to comply through automation and data-driven decision-making (Jin et al., 2023; Qian et al., 2023). At the same time, policy support and clean energy adoption provide fertile ground for digital innovation by generating demand for smart grid technologies, energy management systems, and digital platforms that track carbon footprints. The practical implication is straightforward: governments cannot pursue digital transformation in isolation from environmental objectives, nor can they advance climate goals without investing in digital infrastructure. Smart cities that integrate IoT sensors for traffic management simultaneously reduce congestion and lower emissions, while blockchain-based supply chain traceability enables both efficiency gains and environmental accountability. This suggests that policy frameworks should explicitly link digital infrastructure investments such as broadband expansion and data center efficiency standards with environmental outcomes, embedding sustainability criteria in public procurement for digital technologies.

Renewable energy consumption demonstrates strong bidirectional causality with digital transformation, policy stringency, and overall green economic performance. Beyond its direct environmental benefits of reducing greenhouse gas emissions and enhancing energy security, renewable energy acts as a catalyst for broader economic transformation by stimulating innovation in energy storage, grid flexibility, and distributed generation technologies (Dzwigol et al., 2023;

Murshed, 2020). The feedback mechanism operates through multiple channels: as renewable capacity expands, it lowers energy costs for digital infrastructure (notably energy-intensive data centers), which in turn accelerates digital adoption; simultaneously, successful renewable deployment strengthens political coalitions supporting stringent environmental regulation, creating a self-reinforcing policy cycle. Countries that have aggressively scaled renewable energy such as Denmark in wind power and Germany in solar demonstrate this virtuous cycle, where early investments in clean energy created domestic industries, generated employment, and built constituencies that sustained policy commitment through election cycles. The implication for lagging OECD members is that delayed renewable deployment carries opportunity costs not only in emissions but also in forgone innovation and industrial competitiveness. Policy instruments should therefore prioritize accelerating renewable deployment through streamlined permitting, grid access guarantees, and long-term price signals that reduce investment uncertainty.

The positive effect of environmental policy stringency on green growth, confirmed through both long-run coefficients and bidirectional causality tests, validates the "Porter hypothesis" that well-designed environmental regulation can stimulate innovation and competitiveness rather than merely imposing costs (Gao et al., 2022; Wu et al., 2021). However, effectiveness depends critically on calibration: regulations must be stringent enough to create genuine incentives for behavior change yet flexible enough to avoid stifling entrepreneurship or driving capital flight to jurisdictions with lax standards. Advanced OECD economies possess institutional capacity including enforcement mechanisms, stable legal frameworks, and complementary innovation support that enables them to absorb regulatory costs more effectively than emerging markets. This explains why excessive stringency may harm growth in developing contexts as noted by (Chen et al., 2022) but enhances it in institutionally mature settings where firms can access financing, technical expertise, and legal clarity to comply through innovation rather than evasion. The policy lesson is nuanced: stringency should scale with institutional capacity, and regulators should prioritize outcome-based standards over prescriptive technology mandates to preserve flexibility and encourage diverse pathways to compliance.

The significant causal influence of online public service quality (OSI) on green growth highlights an often-overlooked dimension of sustainability transitions: the role of digital governance infrastructure in reducing transaction costs, enhancing transparency, and enabling citizen participation in environmental policy (Chen and Wang, 2023; Wang and Guo, 2023). E-permitting systems accelerate clean energy project approvals, digital environmental impact assessment portals improve public scrutiny, and open data platforms on emissions enable civil society and investors to hold firms accountable. Countries with high-quality e-government systems Estonia's digital identity infrastructure, Singapore's integrated planning platforms demonstrate how digital governance can de-bottleneck sustainability transitions by removing bureaucratic friction points that delay investment and implementation. For other OECD members, improving OSI requires not merely digitizing existing processes but fundamentally redesigning workflows to prioritize speed, interoperability, and user experience, particularly for green infrastructure projects where lengthy approval timelines increase costs and deter private investment.

The absence of a significant direct relationship between government environmental R&D budgets (RDENV) and green growth stands as the study's most striking and policy-relevant finding. While causality runs from green economic performance to R&D demand (suggesting that growing green sectors pull research investment), the reverse channel from research spending to tangible productivity remains inoperative in the short to medium term. Causality tests reveal that RDENV does not drive renewable energy deployment ($p = 0.3654$) or influence policy stringency ($p = 0.5644$), pointing to a structural disconnect between research outputs and their translation into

applied technologies and regulatory frameworks. This "valley of death" between laboratory research and market deployment is well-documented in innovation studies and reflects several institutional failures. Public environmental research often targets basic science with long commercialization horizons, while private-sector adopters face financing gaps, regulatory uncertainty, and first-mover risks that prevent scaling promising technologies. Moreover, fragmentation across research institutions, policymakers, and industry creates coordination failures where research priorities misalign with market needs or policy objectives.

Addressing this requires rethinking environmental R&D strategy beyond funding levels to focus on diffusion architecture. Effective mechanisms include mission-oriented procurement (where government commits to purchasing novel green technologies at scale), regulatory sandboxes (allowing temporary exemptions to test innovations), standards-setting that creates markets for new solutions, and public-private partnerships with explicit commercialization milestones and co-investment requirements. Denmark's offshore wind success, for instance, combined public R&D with guaranteed feed-in tariffs and domestic content requirements that created a complete innovation ecosystem linking research, manufacturing, and deployment.

The findings collectively point toward the necessity of policy integration rather than siloed interventions. Digital strategies must incorporate environmental performance metrics; renewable energy targets should link to digital infrastructure buildout; environmental regulations should include provisions for e-governance implementation; and R&D programs require explicit diffusion pathways. Institutional coordination mechanisms such as inter-ministerial green growth councils with budget authority can overcome bureaucratic fragmentation that currently impedes coherent policy design.Moreover, the bidirectional causalities identified suggest that timing and sequencing matter. Early digital and renewable investments create positive spillovers that ease subsequent regulatory tightening by lowering compliance costs, whereas premature stringency in the absence of enabling infrastructure may trigger political backlash. Countries at earlier stages of green transition should prioritize foundational investments (broadband, renewable capacity, e-governance platforms) before implementing aggressive regulatory targets, while leaders can focus on optimizing policy mixes and addressing residual barriers such as R&D diffusion gaps.

These results largely confirm established findings while surfacing critical implementation gaps. The positive effects of digitalization, renewable energy, and policy stringency align with Yi et al. (2024), Apergis and Payne (2010), and Fatima et al. (2025), validating these relationships in the OECD context with advanced econometric methods. The bidirectional causalities corroborate recent work by Jin et al. (2023) and Dzwigol et al. (2023) emphasizing mutually reinforcing dynamics among technology, energy, and policy transitions.

However, the RDENV finding diverges sharply from Huang et al. (2022) and Borojo (2024), who identified R&D as a key innovation catalyst. This discrepancy likely reflects methodological differences previous studies often used aggregated innovation metrics or cross-sectional data that obscured implementation lags and highlights a genuine policy challenge: spending alone does not guarantee outcomes. Arjomandi et al. (2023) noted similar crowding-out effects in environmental spending, consistent with the interpretation that premature or poorly targeted R&D investment may divert resources without yielding proportionate returns. The contribution here is demonstrating this disconnect empirically through causality testing and situating it within a broader framework of green growth determinants.

While the analysis focuses on OECD countries, the findings carry lessons for emerging markets navigating their own sustainability transitions. The centrality of digital infrastructure and e-governance suggests that developing countries should prioritize these foundational investments

early, potentially leveraging leapfrogging opportunities (e.g., mobile-based payment systems for renewable energy access) that bypass legacy infrastructure constraints. However, the institutional contingency of policy stringency effects warns against importing OECD-style regulations without parallel capacity-building in enforcement, legal frameworks, and innovation support. International cooperation can accelerate progress by facilitating technology transfer, financing green infrastructure in capital-constrained settings, and harmonizing standards to prevent regulatory arbitrage. Climate finance mechanisms should prioritize integrated packages combining digital, energy, and governance investments rather than narrowly targeted projects, reflecting the interdependencies revealed by the causality analysis. Additionally, knowledge-sharing platforms that document successful R&D diffusion strategies could help countries avoid the implementation gaps observed in advanced economies.

6. Conclusion

This study examined how digital transformation influences green growth trajectories across 35 OECD countries during 2000-2022, employing second-generation panel econometric methods that account for cross-sectional dependence and country-specific heterogeneity. The evidence confirms that sustainable economic development in advanced economies emerges not from isolated interventions but through interconnected mechanisms linking technology adoption, energy transitions, regulatory frameworks, and governance quality.

Digital transformation exerts a measurable positive influence on green productivity, operating through efficiency gains in resource use, optimized energy management systems, and enhanced transparency that enables better environmental monitoring. Renewable energy consumption likewise contributes significantly, not merely by displacing fossil fuels but by catalyzing innovation ecosystems and strengthening political coalitions that support stringent environmental policies. The analysis reveals robust bidirectional causal relationships among digitalization, clean energy deployment, policy stringency, and economic outcomes, suggesting mutually reinforcing dynamics where progress in one domain accelerates advances in others.

Environmental policy stringency proves effective in institutionally mature settings, validating the hypothesis that well-designed regulations stimulate green investment and innovation rather than merely imposing costs. Digital governance platforms captured through the online service index enhance this process by reducing administrative friction, improving transparency, and enabling citizen participation in environmental decision-making. These findings align substantially with recent literature while surfacing a critical implementation gap: government environmental R&D budgets do not translate directly into green productivity gains within observable time horizons. Causality tests confirm this disconnect, showing that research spending fails to drive renewable energy adoption or policy evolution in the short to medium term, likely reflecting delayed commercialization cycles and weak linkages between research institutions, policymakers, and market actors.

For policymakers, the implications are straightforward yet demanding. Effective strategies must integrate digital infrastructure investments with environmental objectives through coordinated planning that embeds sustainability criteria in technology procurement, broadband deployment, and data governance frameworks. Renewable energy targets should link explicitly to digital capabilities smart grids, energy management platforms, and real-time monitoring that enable flexible, efficient systems. Environmental regulation should scale with institutional capacity, prioritizing outcome-based standards that preserve innovation flexibility while maintaining stringency sufficient to incentivize behavioral change. Critically, environmental R&D requires

rethinking beyond funding levels to focus on diffusion architecture: mission-oriented procurement, regulatory sandboxes, standards-setting, and public-private partnerships with explicit commercialization pathways can bridge the gap between laboratory research and market-ready technologies.

The study's limitations point toward future research directions. The OECD focus, while enabling clean causal identification, constrains generalizability to developing contexts where institutional quality, digital divides, and resource constraints create fundamentally different dynamics. Composite indices, though statistically sound, involve measurement trade-offs that merit exploration through alternative proxies AI adoption intensity, digital skill distributions, multidimensional sustainability metrics to test robustness. Sectoral and spatial heterogeneity remain underexplored; green growth drivers likely differ sharply across energy-intensive manufacturing versus services, or between digitally advanced urban centers and peripheral regions facing connectivity gaps. Future work should incorporate firm- and household-level microdata to illuminate micro-mechanisms, employ quasi-experimental designs exploiting policy discontinuities for stronger causal inference, and extend temporal horizons to capture long-run R&D effects as they mature.

Ultimately, the findings underscore that digitalization cannot proceed independently from broader sustainability imperatives. Technology adoption that ignores environmental consequences energy-intensive data centers, electronic waste, resource extraction for devices risks undermining the very goals it purports to advance. Conversely, environmental strategies that neglect digital enablers forfeit opportunities to accelerate transitions through optimization, transparency, and coordination. Green growth emerges where these agendas converge: digital infrastructure designed for energy efficiency, renewable systems managed through smart technologies, environmental regulations enforced via digital platforms, and R&D investments coupled with effective diffusion mechanisms. Achieving this convergence demands institutional coordination across traditionally siloed policy domains, sustained political commitment through electoral cycles, and international cooperation to ensure that advanced-economy lessons inform global sustainability transitions without imposing inappropriate models on diverse contexts.

7. Policy implications and recommendations

Green growth in OECD countries requires coordinated strategies linking digitalization, renewable energy, regulation, and governance rather than isolated interventions. Governments should embed sustainability criteria into digital infrastructure planning by conditioning broadband expansion and data center approvals on energy efficiency benchmarks and renewable sourcing, using public procurement leverage to prioritize environmentally credible suppliers, as Denmark's 100% renewable electricity mandate for data centers and Singapore's Green Data Centre Mark certification demonstrate. Renewable energy targets should link explicitly to smart grid infrastructure and digital monitoring platforms that enable flexible integration, while regulatory barriers can be addressed through digital permitting systems that streamline approvals, as Germany's offshore wind platform showed by cutting timelines 30%. Environmental policy stringency proves effective when calibrated through outcome-based standards rather than prescriptive mandates, with dynamic standards like the EU's sustainability directive providing predictability and transition flexibility, though stringency must scale with institutional capacity to avoid triggering evasion. The absence of direct R&D effects demands explicit diffusion architecture through mission-oriented procurement, public-private partnerships with commercialization milestones, and regulatory sandboxes enabling experimentation, as Denmark's offshore wind

success demonstrates. Whole-of-government coordination through inter-ministerial councils overcomes silos, while timing matters critically: foundational investments in infrastructure should precede aggressive regulatory tightening to build capacity and constituencies.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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