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Artificial Intelligence Readiness and Carbon Productivity in Freight Transport: Evidence from OECD Countries

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Abstract. This study examines whether national artificial intelligence (AI) readiness is associated with a freight-oriented transport carbon productivity proxy in OECD countries. Using a strongly balanced panel of 28 countries for 2020-2022, the dependent variable relates road-and-rail freight transport work, measured in million tonne-kilometers, to national transport-related CO2 emissions. Government AI Readiness is the main explanatory variable, with GDP per capita, renewable energy use, internet penetration, urbanization, and trade openness included as controls. Pooled OLS, fixed-effects (FE), and random-effects (RE) models are estimated with country-clustered standard errors. Correlated random effects/Mundlak, wild cluster bootstrap, and exploratory interaction analyses are added to assess estimator choice, small-cluster inference, and possible complementarity with renewable energy and internet connectivity. The available 2020-2022 data do not identify a statistically significant contemporaneous association between AI readiness and the carbon-productivity proxy. This conclusion is unchanged under within-between decomposition and wild cluster bootstrap inference, while the interaction terms are also statistically insignificant. These null estimates should not be interpreted as evidence of no effect because the short panel, limited within-country variation, construct and outcome measurement limitations, and potentially lagged effects constrain statistical identification.

Keywords: Artificial Intelligence Readiness, Freight Transport, Carbon Productivity, Green Logistics, OECD Countries.

1 Introduction

The decarbonization of transportation has become an increasingly important component of the transition toward sustainable and resource-efficient economies. Freight transportation is particularly relevant in this context because it simultaneously supports

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production, international trade, supply chain integration, and regional connectivity while generating substantial energy demand and environmental pressure. Accordingly, sustainable logistics has evolved beyond the traditional objective of reducing transportation costs toward a broader framework incorporating environmental performance, resource efficiency, digitalization, and long-term economic sustainability. International logistics is therefore increasingly evaluated from an integrated sustainability perspective in which economic performance, environmental responsibility, and technological transformation interact with one another (Çat & Abukalloub, 2025).

The transportation infrastructure also has economic implications that extend beyond logistics operations themselves. Improvements in mobility and infrastructure can affect tourism, local business activity, investment, spatial development, and regional competitiveness. Although sectoral contexts may differ, research on regional economic development has demonstrated that infrastructure investment and increased mobility associated with economic activities can generate wider economic effects through tourism flows, local demand, employment, and urban development. This broader perspective highlights the close relationships among mobility systems, infrastructure quality, and regional productive capacity (Abukalloub & Kutluay Tutar, 2025).

Moreover, transportation and logistics systems are undergoing rapid digital transformation. Artificial intelligence (AI) is increasingly applied to route optimization, demand forecasting, fleet management, predictive maintenance, traffic management, inventory coordination, and real-time logistics decision-making. Such applications have the potential to improve operational efficiency while simultaneously reducing energy consumption and greenhouse gas emissions. Recent studies emphasize that AI can support more efficient vehicle-energy management, traffic optimization, resource allocation, and logistics decision-making, thereby contributing to the environmental sustainability of transport systems (Chen et al., 2024; Miller et al., 2024; Tsolakis et al., 2022).

The environmental implications of AI have also attracted increasing attention at the macroeconomic level. Recent empirical research generally indicates that AI-related technological development can increase carbon efficiency, facilitate energy transition, and improve carbon productivity through innovation, industrial restructuring, and more efficient resource allocation. However, these environmental effects are not necessarily uniform across countries. The magnitude of these effects may depend on complementary factors such as technological development, internet infrastructure, renewable energy availability, environmental regulation, and international trade integration (Wang et al., 2024; Zhang et al., 2026).

An important issue in this literature concerns the measurement of AI. Existing empirical studies frequently rely on AI-related patents, R&D expenditures, technological innovation, industrial robots, or investment indicators. Although such measures capture particular aspects of AI development, they do not necessarily reflect whether a country possesses the broader institutional, technological, governance, and data infrastructure necessary for effective AI deployment. Consequently, technological innovation and actual readiness for AI-enabled transformation should not be treated as identical concepts. This distinction is especially relevant in transportation, where the environmental benefits of AI depend not only on technological availability but also on its effective

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integration into complex physical and institutional systems (Ağan Çelik, 2025; Yuan et al., 2025).

A parallel body of literature examines AI, specifically in transport and logistics. AI-supported technologies have been associated with improved route planning, traffic management, predictive maintenance, port automation, energy efficiency, and supply chain coordination. Empirical and simulation-based studies suggest that intelligent logistics systems can improve operational performance and potentially reduce the carbon footprint of transportation activities. Recent research also indicates that AI can contribute to more sustainable freight transportation and improve broader logistics performance, although these effects often depend on implementation capability, funding, governance, and organizational conditions (Destek et al., 2026; Li & Guangwen, 2025; Moumni et al., 2025; Tsolakis et al., 2022).

Despite these developments, an important gap remains between the macrolevel literature on AI and environmental performance and the sector-specific literature on sustainable logistics. Cross-country studies predominantly examine aggregate carbon emissions, ecological footprints, energy transitions, or economy-wide carbon productivity, whereas transportation studies tend to focus on individual firms, logistics facilities, route-optimization applications, simulations, or specific geographical contexts. As a result, relatively little cross-country evidence directly examines whether broader national AI capabilities are associated with measurable environmental performance, specifically in freight transportation.

A further gap concerns the distinction between AI innovation, realized AI adoption, and AI readiness. Much of the literature asks whether AI innovation, patents, investment, or adoption affect environmental outcomes. Comparatively less attention has been given to whether a country's broader capacity to govern, support, and deploy AI is associated with freight sector environmental performance. This distinction is important for construct validity: national AI readiness is not equivalent to actual AI use by freight operators. In this study, readiness is therefore conceptualized as an upstream enabling condition that may reduce institutional, technological, data, and infrastructure barriers to sectoral AI deployment. The proposed mechanism is sequential: national AI readiness may facilitate sectoral deployment; sectoral deployment may improve route optimization, fleet utilization, predictive maintenance, demand forecasting, and energy management; and these operational improvements may ultimately affect carbon performance. Because the intermediate adoption mechanism is not directly observed, the empirical analysis tests a reduced-form association between national readiness and freight-oriented transport carbon productivity rather than the causal effect of freight-sector AI use.

This study addresses these gaps by examining the relationship between government AI readiness and a freight-oriented transport carbon productivity proxy in OECD countries. Freight transport output is operationalized using road-and-rail tonne-kilometers relative to national transport-related CO_2 emissions, thereby shifting attention from emissions alone toward the amount of freight transport work generated relative to environmental pressure. The GDP per capita, renewable energy use, internet penetration, urbanization, and trade openness are incorporated as controls for broader economic, energy, digital, and structural conditions. Because the emissions denominator also

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contains passenger and other transport emissions, the outcome is explicitly treated as a freight-oriented transport-system proxy rather than a pure freight-sector carbon-efficiency measure.

Using a strongly balanced panel of 28 OECD countries over the 2020-2022 period, the study estimates pooled OLS, FE, and RE models with country-clustered standard errors and year effects. A correlated random-effects (CRE/Mundlak) specification separates within-country and between-country associations and provides a robust estimator-selection test. Wild cluster bootstrap inference is used to assess the sensitivity of key FE p values to the limited number of country clusters. Two exploratory interaction models examine AI readiness × renewable energy and AI readiness × internet penetration. A broader, less harmonized freight measure covering 35 OECD countries and 105 country-year observations is used as an alternative-outcome sensitivity analysis rather than as a strict robustness test.

The study contributes to the literature in three main respects. First, it shifts the empirical focus from AI innovation toward AI readiness while explicitly distinguishing national preparedness from realized freight-sector AI adoption. Second, it introduces a freight-oriented transport carbon-productivity perspective based on comparable road-and-rail transport work and makes the limitations created by the broader national transport-emissions denominator explicit. Third, it bridges macrolevel research on AI and carbon performance with sector-specific sustainable freight research while distinguishing within-country information from between-country information and exploring theoretically motivated complementarity with renewable energy and digital connectivity. Rather than assuming that greater technological readiness automatically produces environmental gains, the study asks whether a statistically detectable contemporaneous association can be identified within the available short panel.

2 Literature Review

Artificial intelligence has increasingly been examined as a potential driver of environmental efficiency and low-carbon transformation. The emerging literature generally argues that AI can improve environmental performance by optimizing resource allocation, facilitating technological innovation, enhancing energy management, and supporting more efficient production and transportation systems. Recent cross-country evidence largely supports this view. Zhang et al. (2026), examining 75 countries, reported that AI technology innovation improves carbon emission efficiency and contributes to narrowing technological efficiency gaps. Similarly, Wang et al. (2024) reported that AI can facilitate energy transition and reduce carbon emissions, although the magnitude of these effects depends on complementary economic conditions such as trade openness. These findings suggest that AI may contribute to decarbonization, but its environmental benefits are unlikely to emerge automatically or uniformly across countries.

A growing strand of research has shifted from conventional carbon emission measures toward carbon productivity and carbon efficiency, thereby emphasizing the amount of economic or productive activity generated relative to environmental pressure. Yuan et al. (2025) reported that AI improves urban carbon productivity through

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mechanisms such as industrial optimization and innovation promotion. Their findings further show that environmental regulation and internet penetration can strengthen the environmental benefits associated with AI. Similarly, Ağan Çelik (2025), who focused on European Union countries, reported that AI-related innovation can positively affect carbon productivity, particularly at lower levels of the carbon-productivity distribution. However, the results also reveal considerable heterogeneity across countries and quantiles. This implies that the AI–carbon productivity relationship may vary according to countries' technological capacity, economic structure, institutional conditions, and stage of environmental development.

This heterogeneity is particularly important when considering how AI is measured. Existing empirical studies frequently rely on indicators such as AI-related patents, research and development expenditures, technological innovation, industrial robots, or AI investment. Such measures capture important aspects of technological development, but they do not necessarily reflect a country's broader ability to govern, support, deploy, and integrate AI technologies. Conversely, a national readiness indicator does not establish that sector-specific firms have actually adopted AI. The present study therefore treats Government AI Readiness as an upstream enabling-environment construct rather than as a proxy for realized freight sector adoption. The hypothesized pathway is AI readiness -> potential for sectoral AI deployment -> operational efficiency -> carbon performance. Only the first and final elements are observed directly in the cross-country dataset, so the intermediate adoption mechanism remains theoretically motivated but empirically unobserved.

The potential environmental role of AI is also increasingly discussed within the areas of transportation and logistics. AI-based technologies can improve route optimization, traffic management, demand forecasting, predictive maintenance, fleet utilization, and energy management. Miller et al. (2024) emphasized that AI applications can improve energy efficiency and reduce greenhouse gas emissions across transport systems. However, they also noted that such benefits depend on data quality, computational requirements, technological integration, and implementation capability. Thus, the availability of AI technologies does not necessarily guarantee environmental improvement unless they are effectively incorporated into existing transportation infrastructures and operational processes.

Evidence from logistics-specific studies further demonstrates the potential contribution of AI to sustainable transportation. Tsolakis et al. (2022) show that AI-supported automation in container terminals can improve operational and environmental performance, illustrating how intelligent logistics technologies may simultaneously increase productivity and sustainability. Similarly, Chen et al. (2024), who reviewed AI applications in sustainable logistics optimization, identified route optimization, resource utilization, real-time decision-making, and emission reduction as major areas in which AI can support greener logistics systems. Studies focusing on AI-driven route optimization also indicate that intelligent transport management can reduce fuel consumption, delivery times, and carbon footprints by improving operational efficiency.

More recent empirical research has moved closer to the intersection between AI, transportation, and sustainability. Destek et al. (2026) reported that AI applications in the transportation sector contribute to reducing carbon emissions in Southeast Asian

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countries, although their results differ across economic sectors. Li et al. (2025), focusing on G20 economies, show that AI positively influences logistics performance, while the strength of the effect varies with AI funding and governance conditions. At the firm level, Moumni et al. (2025) reported that AI integration into freight transportation can improve route planning, energy efficiency, and emission reduction. These studies collectively indicate that AI may generate important sustainability gains in transport and logistics, but they also reveal that the literature is fragmented across country groups, firms, logistics facilities, simulation models, and different measures of AI development.

Another important insight emerging from this literature is that AI's environmental contribution appears to depend on complementary conditions. Internet infrastructure, renewable energy availability, trade openness, human capital, environmental regulation, and institutional quality can influence whether AI capacity translates into environmental improvements. The relevance of renewable energy is also evident in the transportation and broader environmental literature. Evidence from Türkiye highlights the interrelationship among renewable energy, carbon emissions, and economic performance in the logistics sector (Ekici et al., 2024), whereas cross-country panel evidence indicates an important role for the renewable energy transition in carbon emission mitigation across middle- and high-income economies (Kutluay Tutar et al., 2026). For example, Yuan et al. (2025) identify internet penetration as an important condition that strengthens the relationship between AI and carbon productivity, whereas Wang et al. (2024) emphasize the role of trade openness in shaping AI-related environmental outcomes.

Overall, the literature provides substantial theoretical and empirical support for a potential relationship between AI and environmental sustainability. Nevertheless, the evidence is far from uniform. Some studies identify strong positive environmental effects, whereas others reveal nonlinear, conditional, sector specific, or heterogeneous outcomes. Moreover, much of the existing evidence focuses either on economy-wide carbon performance or on specific operational applications of AI within logistics systems. Consequently, there remains considerable scope for research connecting national AI capabilities with measurable environmental performance, specifically in freight transportation.

3 Methodology

3.1 Research Design and Sample

This study employs a short balanced panel design to examine whether national artificial intelligence readiness is associated with freight-oriented carbon productivity in OECD economies. The initial sampling frame comprised all 38 OECD member countries. However, inclusion in the baseline sample required complete and comparable annual observations for Government AI Readiness, road and rail freight activity, transport-related CO_2 emissions, and all control variables for each year from 2020-2022. Applying these complete-case and balanced-panel criteria resulted in a final baseline sample of 28 OECD countries, yielding 84 country-year observations.

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The 28 countries included in the baseline sample are Australia, Austria, Czechia, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Türkiye, and the United States. Belgium, Canada, Chile, Colombia, Costa Rica, Denmark, Greece, Iceland, Israel, and the United Kingdom were excluded because complete road-and-rail freight observations were not available for all three years under the common-data requirement.

The 2020-2022 period is used because it provides the longest common period within the assembled dataset for which AI readiness, the selected freight transport indicators, transport-related CO2 emissions, and the complete set of baseline controls are jointly available without introducing missing observations into the main estimation sample. The resulting main panel is strongly balanced, with three observations for every country and no missing values in the baseline regressions. This time window is determined by common data availability rather than by an assumption that the environmental consequences of AI readiness should materialize within three years. AI-related institutional capacity, infrastructure, organizational adoption, fleet modernization, and logistics-system transformation may operate with substantial lags. Accordingly, the empirical design identifies contemporaneous short-run associations within the available window and should not be interpreted as a test of cumulative or long-run effects.

The empirical design intentionally distinguishes between cross-country differences and changes occurring within the same country over time. This distinction is particularly important because transport infrastructure, geography, modal composition, institutional arrangements, and energy systems differ substantially across OECD countries and may be correlated with both AI readiness and carbon performance. Pooled OLS is therefore reported as a benchmark, whereas the FE and RE estimators account for the panel structure. Because the time dimension is only three years and within-country variation is limited, FE estimates are interpreted specifically as short-run within-country associations rather than as the sole basis for inference. CRE/Mundlak estimates are additionally used to separate within-country and between-country components.

3.2 Variable Construction and Data Sources

The main explanatory variable is the Government AI Readiness Index published by Oxford Insights. The index captures national-level institutional, technological, data, and infrastructure conditions relevant to AI readiness and is therefore used as a measure of the broader enabling environment for AI-related transformation. It does not measure realized AI adoption or the intensity of AI use within freight transportation. A higher readiness score may indicate conditions that facilitate deployment, but it does not imply that freight operators use AI-supported routing, predictive maintenance, fleet management, or energy-optimization technologies. Consequently, the AI-readiness coefficient is interpreted as the association between national preparedness and the freight-oriented transport carbon productivity proxy, not as the causal effect of sector-specific AI use. Direct validation of the intermediate freight-adoption mechanism would require

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harmonized cross-country measures of freight-sector AI adoption, which are not available consistently across countries and years.

The dependent variable is a freight-oriented transport carbon productivity proxy. Freight activity is measured via annual road and rail freight transport data from the OECD/International Transport Forum (ITF), expressed in million tonnes. A tonne-kilometer represents the transport of one tonne of goods over one kilometer and therefore captures both freight weight and transport distance. This is preferable to simple tonnage for measuring transport work and for comparing countries with very different average transport distances and geographical structures. Road and rail are used in the baseline specification because they provide the most comparable common modal coverage across the countries retained in the balanced sample. The numerator is converted from million tonnes to tonnes and divided by national transport-related CO_2 emissions measured in tonnes.

$$FCP\_it = [(Road\_tkm\_it + Rail\_tkm\_it) \times 1{,}000{,}000]/Transport\_CO2\_it$$

The resulting indicator is expressed as tonne-kilometers of observed road-and-rail freight transport work per tonne of national transport-related CO_2 emissions. Its natural logarithm, ln(FCP), is used as the primary dependent variable. The logarithmic transformation reduces scale differences across countries and allows coefficients on continuous regressors to be interpreted in percentage terms where appropriate.

An important measurement qualification concerns the emissions denominator. Although the numerator captures road-and-rail freight transport work, the denominator represents total national transport-related CO_2 emissions and therefore also contains emissions generated by passenger and other transport activities. The constructed indicator should consequently not be interpreted as direct freight-specific carbon productivity or freight emission intensity. Instead, it measures observed freight transport work relative to the overall carbon burden of the national transport system. This mismatch can affect cross-country comparability because passenger-freight structures, modal compositions, vehicle fleets, mobility patterns, and energy systems differ across OECD economies. For example, a country with relatively high passenger-transport emissions may have a lower value of the proxy even when freight operational efficiency is similar to that of another country. The resulting measurement error may therefore be nonnegligible and heterogeneous across countries. The proxy is retained because harmonized annual freight-specific CO_2 emissions corresponding to the modal freight data are not consistently available for the full sample and study period; all results are interpreted with this qualification.

The baseline models include five controls. The GDP per capita in PPP-adjusted constant international dollars is included in natural logarithms to account for differences in economic development. The renewable energy share captures differences in the energy structure. Internet use proxies the breadth of digital connectivity, urbanization captures spatial and transport-demand characteristics, and trade openness (trade as a percentage of GDP) controls for exposure to international commerce and freight demand. The underlying control series were assembled from World Bank-compatible datasets distributed through our World in Data, whereas the transport CO_2 series was obtained from the Climate Watch/Our World in Data transport emissions series used in the project dataset.

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3.3 Econometric Specification

The baseline empirical relationship is specified as follows:

ln(FCP_it) = beta_0 + beta_1 AI_it + beta_2 ln(GDPpc_it) + beta_3 REN_it + beta_4 INT_it + beta_5 URB_it + beta_6 TRADE_it + mu_i + lambda_t + epsilon_it

where i represents countries and t represents years. AI denotes the Government AI Readiness score; GDPpc is PPP-adjusted GDP per capita; REN is the renewable energy share; INT is internet use; URB is the urban population share; and TRADE is trade openness. The term mu_i captures time-invariant country-specific heterogeneity, lambda_t represents common year effects, and epsilon_it is the idiosyncratic error term.

All reported baseline panel specifications include year effects, with 2020 serving as the reference year. Standard errors in pooled OLS, FE, and RE models are clustered at the country level to allow for arbitrary within-country correlation and heteroskedasticity. Given the limited time dimension, the analysis focuses on static panel estimators rather than dynamic panels, unit roots, cointegration, or long-run specifications. The coefficients are therefore interpreted as contemporaneous associations rather than long-run causal effects. Because the baseline contains only 28 country clusters, conventional cluster-robust inference is supplemented with wild cluster bootstrap-t tests for key FE coefficients via 9,999 replications, Rademacher weights, and a fixed seed for reproducibility.

3.4 Diagnostic Tests and Estimator Choice

Several diagnostic checks were conducted before the panel estimates were interpreted. The pairwise correlations among the explanatory variables remain below 0.80; the largest observed correlation is 0.701 between GDP per capita and internet use. The variance inflation factors range from 1.14-4.17, with a mean variance inflation factor (VIF) of 2.19, indicating that multicollinearity is not a serious concern under the conventional threshold of 5.

The panel structure is strongly supported by the specification tests. The Breusch–Pagan Lagrange multiplier test rejects the null of zero panel-level variance, whereas the joint test of country fixed effects rejects the hypothesis that all country effects are equal to zero. The estimated intraclass correlations are also very high, indicating that persistent country-specific heterogeneity accounts for a substantial share of the composite unexplained variance.

The conventional Hausman comparison generates a nonpositive-definite variance–difference matrix and a rank warning and is therefore not used as the principal estimator–selection criterion. Instead, a correlated random-effects (Mundlak) specification augments the RE model with country-specific means of all time-varying regressors. A joint Wald test of these country means yields chi2(6) = 6.48 (p = 0.3714), so the null hypothesis that the observed regressors are uncorrelated with the unobserved country-specific effects cannot be rejected. This result provides no statistical evidence against the conventional RE orthogonality assumption, although failure to reject it is not interpreted as proof that the assumption necessarily holds in such a short panel. The FE, RE,

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and CRE results are therefore treated as complementary rather than as competing estimates selected mechanically by a single test.

The within-between decomposition further informs interpretation. For AI readiness, the between-country standard deviation is 8.216, whereas the within-country standard deviation is 2.099. For log freight-oriented transport carbon productivity, the within-country standard deviation is only 0.054. Thus, most of the identifying information for FE comes from a narrow range of short-run within-country changes. The very high intraclass correlation should not be interpreted as meaning that approximately 99% of the observed variation in every variable is between countries; rather, it concerns the share of composite error variance attributable to persistent country effects. Nevertheless, when considered together with the descriptive within-between decomposition, this confirms the limited information for precise FE identification. A CRE within-between model is therefore used to estimate within-country deviations and conditional country-mean components separately.

3.5 Alternative Outcome and Sensitivity Strategies

An alternative-outcome FE specification uses a broader freight carbon productivity numerator. Instead of restricting the numerator to roads and rails, it sums the freight modes reported for each country (rail, road, inland waterways, and pipeline, where available) and divides this total transport work by national transport-related CO2 emissions. Under this less restrictive data criterion, 35 of the 38 OECD countries have complete observations for 2020-2022, producing a strongly balanced sensitivity sample of 105 country-year observations; Colombia, Costa Rica, and Denmark remain excluded because no complete usable freight series are available for all three years.

This broader specification increases country coverage but does not provide a fully harmonized multimodal outcome. Some countries report only roads and rails, whereas others additionally report inland waterway and/or pipeline freight. It therefore trades measurement comparability for sample coverage and is not treated as a strict robustness test on the basis of an identically constructed dependent variable. The baseline road-and-rail measure remains the preferred outcome because its modal definition is common across the 28-country baseline sample.

The broader specification is used only as an alternative-outcome sensitivity analysis to determine whether the central statistical inference regarding AI readiness is overturned when additional reported freight activity and countries are incorporated. Because the modal composition differs across countries, changes in the sign or magnitude of the coefficient are not interpreted as evidence of coefficient stability. In addition, small-cluster inference is assessed with wild cluster bootstrap-t tests, and theoretically motivated interaction models are used to examine whether renewable energy or general internet connectivity moderates the AI-readiness association. Formal threshold models are not estimated because reliable threshold identification places substantially greater demands on a dataset containing only 84 baseline observations and three time periods.

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3.6 Exploratory Complementarity Specification

To examine whether national AI readiness is associated with carbon productivity only under complementary conditions, two parsimonious FE interaction models are estimated separately: AI readiness × renewable energy share and AI readiness × internet penetration. AI readiness and the respective moderator are mean-centered before each interaction is constructed. Separate models are used to limit parameter proliferation in the short panel. The interaction coefficients are evaluated via both country-clustered inference and wild cluster bootstrap-t tests with 9,999 replications. These specifications are treated as exploratory mechanism tests rather than definitive causal evidence because interaction effects are particularly difficult to identify with limited within-country variation.

4 Findings

4.1 Descriptive Evidence

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
ln(Freight-Oriented Transport Carbon Productivity)	7.955	0.595	6.999	9.382
AI Readiness	68.638	8.384	46.010	88.160
ln(GDP per capita, PPP)	10.863	0.384	9.890	11.826
Renewable Energy (%)	24.227	14.712	3.580	61.670
Internet Use (%)	89.379	6.268	70.483	99.000
Urbanization (%)	76.081	11.320	53.190	94.986
Trade Openness (% of GDP)	116.354	75.113	23.140	412.177

Note. The sample is a strongly balanced panel of 28 OECD countries observed from 2020-2022. Freight-oriented transport carbon productivity is the natural logarithm of road-and-rail freight transport work (tonne-kilometers) per tonne of national transport-related CO_2 emissions. N = 84.

Table 1 shows meaningful variation in both the dependent and explanatory variables. AI readiness ranges from 46.01-88.16, whereas renewable energy use and trade openness display particularly pronounced dispersion across OECD economies. Internet penetration is high on average but remains sufficiently heterogeneous for empirical analysis. The variation observed in the main variables supports the subsequent panel estimations, although the within-between decomposition indicates that much of this variation is cross-sectional rather than temporal.

4.2 Baseline Panel Estimates and Alternative-Outcome Sensitivity

Table 2. Main Panel Estimates and Alternative Outcome Sensitivity Analysis

Variables	(1) Pooled OLS	(2) FE	(3) RE	(4) Alternative Outcome FE

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AI Readiness	0.0019 (0.0156)	-0.0015 (0.0054)	-0.0024 (0.0045)	0.0202 (0.0234)
ln(GDP per capita, PPP)	-0.9433** (0.3735)	-0.6905 (0.7552)	-0.6267** (0.3030)	-3.7458 (2.9531)
Renewable Energy (%)	0.0091 (0.0075)	0.0140* (0.0074)	0.0130*** (0.0045)	0.0241 (0.0222)
Internet Use (%)	0.0251 (0.0236)	-0.0006 (0.0040)	-0.0001 (0.0036)	0.0101 (0.0134)
Urbanization (%)	-0.0036 (0.0094)	0.0269 (0.0171)	0.0009 (0.0097)	0.0784 (0.0486)
Trade Openness (% of GDP)	0.0005 (0.0016)	-0.0009 (0.0011)	-0.0004 (0.0008)	0.0026 (0.0051)
Year effects	Yes	Yes	Yes	Yes
Country effects	No	Fixed	Random	Fixed
Country-clustered SE	Yes	Yes	Yes	Yes
Observations	84	84	84	105
Countries	28	28	28	35
R2/Within R2	0.246	0.219	0.205	0.159
Model p value	0.0009	0.0001	<0.001	0.0174

Notes. Country-clustered standard errors are reported in parentheses. All the models include year effects. Models (1)-(3) use the common road-and-rail freight-oriented transport carbon productivity proxy; Model (4) uses the broader reported-modes alternative outcome and is interpreted as a sensitivity analysis rather than a strictly harmonized robustness test. For the FE and RE models, the displayed R2 is within R2. Conventional clustered significance levels are shown as * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Small-cluster wild bootstrap inference for key FE coefficients is reported separately in Table 5.

The central empirical result is that the available data do not identify a statistically significant contemporaneous association between national AI readiness and the freight-oriented transport carbon productivity proxy. The AI coefficient is small and insignificant in clustered pooled OLS (beta = 0.0019, p = 0.903), slightly negative and insignificant in FE (beta = -0.0015, p = 0.788), and negative and insignificant in RE (beta = -0.0024, p = 0.598). The sign is therefore not stable across all specifications, and none of the estimates is statistically distinguishable from zero. Given the short time window, weak within-country variation, and measurement limitations, this result is interpreted as an absence of a statistically detectable short-term association, not as affirmative evidence that AI readiness has no effect.

The GDP per capita coefficient is negative and statistically significant in pooled OLS (beta = -0.9433, p = 0.018) and RE (beta = -0.6267, p = 0.039) but loses significance under FE (beta = -0.6905, p = 0.369). Because both GDP per capita and the dependent variable are expressed in natural logarithms, the pooled coefficient implies an elasticity of approximately -0.94. The disappearance of statistical significance in the FE model suggests that this negative association is largely related to persistent cross-country differences rather than short-term changes within countries.

Renewable energy use has a positive coefficient across the principal panel specifications. Under conventional clustered inference, it is insignificant in pooled OLS (beta

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= 0.0091, p = 0.234), marginally significant in FE (beta = 0.0140, p = 0.068), and statistically significant in RE (beta = 0.0130, p = 0.004). However, the apparent marginal FE significance does not survive the small-cluster correction: the wild cluster bootstrap p value is 0.1263, and the 95% confidence set includes zero. The broader alternative-outcome specification is also statistically insignificant. Renewable energy is therefore treated as directionally positive but not robustly established.

Internet use, urbanization, and trade openness are statistically insignificant in the main clustered panel specifications. The 2021 year effect is positive and significant in the RE model but not in the pooled OLS or FE, and the 2022 effect is insignificant throughout. Consequently, no common year effect is interpreted as robust across estimators.

The alternative-outcome FE specification expands the sample to 35 countries and 105 observations using all reported freight modes available for each country. Because modal coverage is not identical across countries, this model is interpreted as a sensitivity analysis rather than as a strict harmonized robustness test. The AI-readiness coefficient becomes positive (beta = 0.0202) but remains statistically insignificant (p = 0.395). The exercise therefore does not establish sign or coefficient stability; it only shows that the central conclusion of no statistically detectable AI–readiness association is not overturned when broader, but less comparable, freight coverage is used.

4.3 Diagnostic and Estimator-Selection Results

Table 3. Diagnostic and Model Specification Tests

Diagnostic/Test	Statistic	p value	Interpretation
Maximum VIF	4.17	-	No serious multicollinearity
Mean VIF	2.19	-	No serious multicollinearity
Maximum pairwise correlation	0.701	-	Below 0.80
Breusch–Pagan LM test	chibar2 = 80.24	<0.001	Panel variance is present
Joint test of country FE	F(27,48) = 209.83	<0.001	Country effects jointly significant
Mundlak specification test	chi2(6) = 6.48	0.3714	RE orthogonality not rejected
FE intraclass correlation	rho = 0.9905	-	Very strong country heterogeneity
RE intraclass correlation	rho = 0.9889	-	Very strong country heterogeneity

Note. The conventional Hausman statistic is not used as the principal estimator-selection criterion because Stata reports a nonpositive-definite variance-difference matrix and a rank warning. The Mundlak test is based on the joint significance of country means of the time-varying regressors in a correlated random-effects specification estimated with country-clustered standard errors.

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The diagnostic results confirm that the panel structure is empirically important. The Breusch–Pagan LM test strongly rejects the null hypothesis of no panel-level variance, and the joint FE test strongly rejects the hypothesis that all country effects are zero. The intraclass correlation is approximately 0.99 in both the FE and RE models, showing that persistent country-specific heterogeneity accounts for an exceptionally large share of the composite unexplained variance. This high rho does not mean that 99% of each observed variable's variance is between countries, but it reinforces the importance of persistent national factors when interpreted together with the within-between decomposition.

The multicollinearity diagnostics are reassuring: the maximum VIF is 4.17, the mean VIF is 2.19, and the largest pairwise correlation among the explanatory variables is 0.701. The conventional Hausman comparison is not treated as decisive because of the variance-difference matrix warning. The robust Mundlak test instead yields chi2(6) = 6.48 (p = 0.3714), so the RE orthogonality assumption is not rejected. Nevertheless, given the short panel, the FE, RE, and CRE results are retained as complementary evidence rather than interpret failure to reject the Mundlak null as a definitive proof of RE exogeneity.

4.4 Within-Between Decomposition and Small-Cluster Inference

Table 4. Correlated Random Effects Within-Between Decomposition

Variable	Within component	Between component
AI Readiness	-0.0015 (0.0056)	0.0028 (0.0192)
ln(GDP per capita, PPP)	-0.6905 (0.7874)	-0.9918** (0.4279)
Renewable Energy (%)	0.0140* (0.0077)	0.0088 (0.0081)
Internet Use (%)	-0.0006 (0.0042)	0.0286 (0.0287)
Urbanization (%)	0.0269 (0.0178)	-0.0040 (0.0098)
Trade Openness (% of GDP)	-0.0009 (0.0012)	0.0005 (0.0018)
Year effects	Yes	Yes
Observations	84	84
Countries	28	28

Notes. Country-clustered standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$. The within component captures deviations from country means; the between component captures conditional country-mean differences. rho = 0.9906. Wald test of AI within = between: chi2(1) = 0.05, p = 0.8269.

The CRE decomposition directly addresses whether the high intraclass correlation makes the FE result uninformative about the broader cross-country relationship. The within-country AI-readiness coefficient is -0.0015 (p = 0.794), whereas the conditional between-country coefficient is 0.0028 (p = 0.886). Neither component is statistically significant, and a Wald test fails to reject the equality of the within and between

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coefficients (chi2(1) = 0.05, p = 0.8269). Thus, the absence of a statistically detectable AI-readiness association is not confined to the limited within-country variation used by FE; the larger cross-country component also does not reveal a significant conditional association. In contrast, GDP per capita is insignificant within countries (beta = -0.6905, p = 0.380) but negative and significant between countries (beta = -0.9918, p = 0.020), supporting the interpretation that its negative association in pooled OLS and RE largely reflects persistent cross-country differences.

Table 5. Small-Cluster Wild Bootstrap Inference for Key FE Coefficients

Variable	FE coefficient	Clustered p	WCB p	WCB 95% confidence set
AI Readiness	-0.0015	0.788	0.8174	[-0.01515, 0.01017]
Renewable Energy (%)	0.0140	0.068	0.1263	[-0.005719, 0.03099]

Note. Wild cluster bootstrap-t inference uses 9,999 replications, Rademacher weights, country-level clustering, and a fixed random seed. WCB = wild cluster bootstrap.

Small-cluster inference leaves the principal AI conclusion unchanged. The conventional FE p value for AI readiness is 0.788, whereas the wild cluster bootstrap p value is 0.8174, and the 95% confidence set comfortably includes zero. The correction is more consequential for renewable energy: its conventional clustered p value of 0.068 increases to 0.1263 under the wild bootstrap. Accordingly, the previously marginal renewable energy result is not treated as statistically robust. The wild bootstrap addresses finite-cluster inference but does not solve the separate limitation created by the three-year time dimension and weak within-country variation.

Taken together, the baseline, CRE, and small-cluster results do not identify a statistically detectable contemporaneous relationship between broad national AI readiness and the freight-oriented transport carbon productivity proxy in OECD countries from 2020-2022. The coefficient remains statistically insignificant across pooled OLS, FE, RE, within-between decomposition, and wild cluster bootstrap inference, although its sign is not stable across every outcome construction. These results should not be interpreted as evidence that AI readiness has no environmental effect; rather, they show that the present short-panel design does not reliably detect such an association.

The results also highlight the importance of structural country characteristics. The high intraclass correlation and the significant between-country GDP component indicate that persistent national differences matter substantially. Renewable energy remains directionally positive in several models, but its FE significance is not robust to wild cluster bootstrap inference. This pattern motivates the additional question of whether AI readiness operates conditionally on complementary energy or digital infrastructure rather than through an unconditional linear association.

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4.5 Exploratory Complementarity Analysis

Table 6. Exploratory Interaction Tests

Interaction	Coefficient	Clustered p	WCB p	WCB 95% confidence set
AI Readiness x Renewable Energy	-0.000325	0.215	0.4303	[-0.0008164, 0.0009526]
AI Readiness x internet Penetration	-0.000304	0.574	0.6475	[-0.001738, 0.0009257]

Notes. Fixed-effects models include year effects and the baseline controls. AI readiness and the respective moderator are mean-centered before interaction. WCB inference uses 9,999 replications, Rademacher weights, and country-level clustering.

Neither exploratory interaction provides statistically significant evidence of complementarity in the available short panel. The AI readiness × renewable energy interaction is negative but insignificant under conventional clustered inference (beta = -0.000325, p = 0.215) and wild cluster bootstrap inference (p = 0.4303). Marginal effect calculations at renewable energy shares of approximately 14.2%, 24.2%, 34.2%, and 44.2% likewise leave the AI readiness effect statistically indistinguishable from zero (p = 0.864, 0.646, 0.402, and 0.309, respectively). The AI readiness × internet penetration interaction is also statistically insignificant (beta = -0.000304, clustered p = 0.574; wild bootstrap p = 0.6475). These estimates therefore provide no detectable evidence of short-run moderation by renewable energy or general internet connectivity, but they do not establish that complementary mechanisms are absent. Interaction effects are particularly difficult to identify, with only three observations per country and limited within-country movement in the underlying variables.

5 Conclusion

This study examined whether national artificial intelligence readiness is associated with a freight-oriented transport carbon productivity proxy in OECD countries. Using a strongly balanced panel of 28 OECD economies from 2020-2022, the analysis combines Government AI Readiness with road-and-rail freight transport work measured in tonne kilometers, national transport-related CO_2 emissions, and a set of economic, energy, digital, and structural controls. Pooled OLS, FE, and RE estimators are complemented by CRE/Mundlak within-between analysis, wild cluster bootstrap inference, and exploratory interaction tests. A broader reported-modes outcome expands the sensitivity sample to 35 countries and 105 country-year observations but is explicitly treated as less harmonized than the baseline measure.

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The central empirical finding is that the available three-year panel does not identify a statistically significant contemporaneous association between national AI readiness and freight-oriented transport carbon productivity. The AI-readiness coefficient is insignificant in pooled OLS, FE, and RE specifications, remains insignificant in the CRE within and between components, and is unchanged substantively under wild cluster bootstrap inference. The broader alternative-outcome specification likewise does not identify a significant association. This pattern should not be interpreted as affirmative evidence of a zero effect. The short observation window, limited within-country variation, measurement limitations, and potentially lagged implementation effects prevent the present design from distinguishing confidently between a genuinely weak short-run relationship and an effect that is not detectable with the available data.

The distinction between national AI readiness and realized freight sector AI adoption is central to this interpretation. AI can potentially improve routing, forecasting, traffic management, fleet utilization, predictive maintenance, and energy management, but the Government AI Readiness Index measures the broader national enabling environment rather than the actual use of these technologies by freight operators. The empirical model therefore does not test the operational adoption mechanism directly. A statistically insignificant readiness coefficient may reflect a gap between national capacity and sectoral implementation, but the present data cannot establish that mechanism causally.

Among the controls, renewable energy has a generally positive coefficient, but its statistical evidence is not robust. In particular, the marginal significance observed under conventional clustered FE inference disappears under wild cluster bootstrap inference ($p = 0.1263$). The result should therefore be viewed as directionally suggestive rather than statistically established. The GDP per capita is negative in pooled OLS and RE but insignificant within countries; the CRE decomposition shows a significant negative between-country component, indicating that this pattern primarily reflects persistent cross-country differences rather than short-run within-country changes.

The exceptionally high intraclass correlation further emphasizes the importance of persistent country-specific heterogeneity, although rho should be interpreted as a variance-component statistic rather than as the percentage of observed variation in every variable that occurs between countries. The additional within-between model confirms that the insignificant AI result is not merely a consequence of relying on limited FE variation: the conditional between-country AI component is also statistically insignificant. Moreover, the short time dimension remains a fundamental limitation for statistical power and for the ability to study delayed environmental effects.

Policy implications should therefore be framed cautiously. The estimates do not justify the conclusion that improving national AI readiness will fail to generate environmental benefits, nor will they establish that readiness alone is sufficient. Instead, they indicate that no measurable contemporaneous association is detected in the available 2020-2022 panel. Policies that link national AI capacity with sector-specific deployment, interoperable transport data, freight system modernization, low-carbon energy, and operational applications such as intelligent routing, predictive maintenance, and multimodal coordination remain theoretically relevant, but their environmental effects require stronger sector-specific and longer-horizon evidence.

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Several limitations should be acknowledged. First, the 2020-2022 period provides only three annual observations per country, producing limited within-country variation and low power for identifying effects that emerge gradually or with implementation lags. Second, government AI readiness measures national preparedness rather than realized AI adoption within freight transportation, so the intermediate sector-specific mechanism remains unobserved. Third, the dependent variable is a freight-oriented transport carbon productivity proxy: the numerator uses road-and-rail tonne-kilometers, whereas the denominator contains total national transport-related CO2 emissions, including passenger and other transport emissions. Differences in passenger-freight structures and modal composition can therefore introduce nonnegligible cross-country measurement heterogeneity. Fourth, the alternative 35-country outcome increases coverage by summing different reported modal combinations and is consequently less harmonized than the baseline road-and-rail measure. Fifth, the statistically insignificant AI coefficient cannot distinguish a substantively absent effect from an effect that the present design is unable to detect because of low power, measurement error, weak within-country variation, heterogeneous effects, or delayed adjustment. Finally, the analysis focuses on OECD economies, limiting generalizability to developing and emerging transport systems.

Future research should revisit this relationship as additional harmonized annual data become available, allowing the common observation window to extend beyond the current 2020–2022 period. Longer panels may also become feasible if comparable historical series for freight transport activity, freight-related emissions, and AI-related capacity can be constructed from alternative data sources. Future studies should further incorporate direct measures of AI adoption in logistics and transportation and, where available, freight-specific CO_2 emissions. A longer common data window would permit a more credible examination of lagged responses, nonlinearities, and formal threshold effects. The exploratory interactions estimated in this study do not identify significant moderation by renewable energy or general internet penetration, but these results should be reassessed when greater temporal variation and statistical power become available. Future research could also examine sector-specific transport digitalization, modal differences, infrastructure readiness, and whether the environmental returns to AI emerge only after particular levels of technology adoption or clean-energy penetration are reached.

Overall, the findings do not support the claim that AI readiness has no environmental effect. Rather, the available short panel does not provide statistically significant evidence of a contemporaneous association between national AI readiness and freight-oriented transport carbon productivity, either unconditionally or through exploratory renewable-energy and internet-connectivity interactions. The environmental implications of AI are likely to depend on how national technological capacity is translated into sector-specific applications over time. Establishing these relationships more convincingly will require richer longitudinal evidence as additional comparable observations become available, together with direct measures of freight-sector AI adoption and more closely matched freight-specific emissions data.

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

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The language editing of this manuscript was assisted by Grammarly, used solely for grammatical improvements. The scientific content remains the sole responsibility of the authors.

Research Ethics

Ethical review and approval were not required for this study because it involved the analysis of publicly available, previously published data and did not involve human participants.

Informed Consent Statement

Not applicable.

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