



ARTIFICIAL INTELLIGENCE ADOPTION, MANUFACTURING ENERGY INTENSITY, AND R&D EXPENDITURE ON GREEN MANUFACTURING PERFORMANCE: THE MODERATING ROLE OF ENVIRONMENTAL POLICY STRINGENCY

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ABSTRACT

Purpose: This research investigates the contingent impacts of artificial intelligence (AI) adoption, the energy intensity of manufacturing, and the national research and development (R&D) spending on green manufacturing performance in 30 countries in the period of 2015-24 with the theorized moderating variable being environmental policy stringency (EPS).

Design/methodology/approach: The study is based on the Resource-Based View (RBV) and the Technology-Organization-Environment (TOE) paradigm and involves compilation of a 30-country balanced panel based on the Oxford Insights Government AI Readiness Index, International Energy Agency (IEA) energy data, World Bank World Development Indicators (WDI), OECD Environmental Policy Stringency (EPS) database, and a home cooked Green Manufacturing Performance Index. The main estimator used is the fixed effects (FE) regression using Driscoll-Kraay standard errors; random effects and Hausman tests are used as robustness checks. Sub-sample tests examine the heterogeneity of income-groups of people, and moderation is tested using interaction terms.

Findings: EAI and R&D investment has a large positive impact on green manufacturing performance, which is significant whereas manufacturing energy intensity has a large negative impact. The AI adoption-green manufacturing nexus is positively mediated by environmental policy stringency, which suggests AI technologies are stimulated to open their latent environmental potential.

Research limitations/implications: The composite nature of the Green Manufacturing Performance Index and aggregate annual data on adoption the level of AI may pose imprecision in measurement. Digital industrial strategies must be optimally counter-balanced by environmental regulation to ensure that the green dividend of the AI-based transformation of manufacturing is optimized.

Keywords: AI Adoption; Green Manufacturing; Energy Intensity; R&D Expenditure; Environmental Policy Stringency; Fixed Effects; Panel Data

1. INTRODUCTION

The world economy manufacturing industry is at a great turning point and facing both the dual demands of the digital transformation and decarbonization, the manufacturers and the governmental bodies that control them should determine how to balance the complicated relationships between the new technologies, especially artificial intelligence, and the effects of

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industrial production on the environment (Huang et al., 2023). AI is permeating the chain of manufacturing, in predictive maintenance, which would reduce energy waste, in generative design, which would reduce material use, in intelligent logistics, which would reduce fleet emissions, and in real-time process control, which would turn raw energy input into useful product at an efficiency never previously observed (Xu, 2026). However, the eco-beneficial potential of AI in production is still mostly theoretical with no underlying conditions of regulatory pressure, research potential, and institutional preparedness that transform tech possibilities into environmental fact (Zhao & Liu, 2026).

This study evaluates three country-level determinants of the green manufacturing performance. Understandably, the first measure is AI adoption, as it can be determined as the Oxford Insights Government AI Readiness Index that is a systemic indicator of whether a particular national economy is prepared to utilize and enjoy the advantages of AI technologies in every sphere including manufacturing (Zhou & Bu, 2026). Second, the manufacturing energy intensity, a ratio of the amount of energy used to the amount of manufacturing output, is a productive input variable and an indicator of environmental performance, which measures the extent to which the industrial processes have been decoupled with the reliance on fossil fuels (Yang, 2026). Third, the national R & D expenditure as a percentage of the GDP is used to measure the innovation capacity that helps nations to invent, adapt and propagate the clean technologies that support green manufacturing transitions (Yu, 2026). Collectively, the three predictors cover the technological, operational and innovation dimension of industrial sustainability.

The key theoretical hypothesis of the given paper is that the beneficial environmental impact of AI adoption is not unconditional. High Technology-Organization-Environment (TOE) model with predicts organizational and environmental environments mediate and moderate adaptation and influence of technologies (Huang et al., 2023). The most salient environmental-context variable, at the country level, to manufacturing decarbonization is the environmental policy stringency (EPS) the composite OECD indicator of both market-based and non-market-based environmental regulations (IEA, 2023). Moderation logics Moderation logics are simple in the countries where environmental control is strict, the manufacturers have bigger incentives to use AI capabilities to exploit energy optimization, waste minimization, and emissions regulation (OECD, 2023). In those nations with low regulatory pressure, the energy-reducing and emissions-cutting potential of AI can be latent, with the companies not feeling enough pressure to implement AI with the goal of green effect, and not necessarily with the aim of achieving productivity (Gao et al., 2022).

This paper is important to the literature in the following aspects. First, it is an advancement of the macro-level industrial ecology literature by developing and empirically validating a composite Green Manufacturing Performance Index based on CO₂ intensity, share of renewable energy in manufacturing, and eco-innovation scores, more of an outcome measure than the single-variable proxies used in other literature. Second, it unconditionally evaluates the moderation hypothesis through interaction functions within a stringent fixed effect modelling with Driscoll-Kraay standard fallacies, both the reliance on transcendence and serial correlation. The econometric limitations have been somewhat unsuccessful in similar research. Thirdly, the results of sub-sample analysis in relation to income groups show how AI is conditional in giving green dividend, a subtle piece of advice to both advanced and emerging economies.



2. LITERATURE REVIEW

2.1 Artificial Intelligence and Environment Results.

Artificial intelligence and environmental performance have been the subject of increasingly popular scholarly investigation since the landmark review of 93 UN Sustainable Development Goals targets by (Pan et al., 2022), which determined that AI could support 134 goals and could potentially suppress 59 goals. Within the manufacturing environment, environmental capabilities of AI are found in 3 functional domains namely energy management, process optimization and supply chain sustainability. (Ma et al., 2021) perform a literature review on AIs and sustainability and find energy consumption reduction to be the most commonly reported environmental benefit, which is explained by the ability of AI to reveal waste and inefficiency trends that cannot be recognized by a human operator at scale. (Dauvergne, 2020) empirically makes some important counterpoints stating that AI technologies themselves have large energy and resource footprints, i.e. training and operation of large AI models have large electricity footprint and also that rebound effects could wipe net environmental benefits away or counteract them, in case AI-enabled efficiency gains do encourage higher overall production volumes.

The national environmental outcomes can be studied using AI adoption indices that are only nascent and yet enlightening at the country level. (Nishant et al., 2020) focuses on the correlation between AI-related patent applications and carbon emissions in 30 countries of the OECD and suggests that there is a strong negative correlation, which is also in line with the idea of AI promoting green innovation. (Vinueza et al., 2020) also utilize a difference-in-differences study that involves the New Generation AI Development Plan in China as a quasi-natural experiment and conclude that the decrease in energy intensity and pollution intensity in cities developing into AI pilot zones compared with similar control cities is significantly faster, which can be taken as causal proof of the environmental benefits of AI in a condition of strong policy-forming environments, which directly inspires moderation hypothesis of the current study.

2.2 Production of Energy Intensity and Green Transition

One of the most common proxies used to measure the environmental performance of industries is manufacturing energy intensity as the amount of energy that is used per unit of manufacturing value added (Noailly & Smeets, 2015). This decrease in energy intensity in industrialized economies was consistently recorded in the empirical literature, which is steered by the structural change in favors of the disappearance of energy-intensive industries in favor of knowledge-intensive ones, introduction of energy efficient technology, and increased energy prices (Ambec et al., 2013). Nevertheless, the growth rate of the intensity has decreased in most developed economies since 2015, and in a number of emerging economies intensity of energy has started to stagnate or even rise faster than can be matched by investment in energy efficiency (IEA, 2023). The cross-country causes of energy intensity variation and specifically the form of digital technologies (AI) is, consequently, a policy-relevant research question, the implications of which, directly, are applicable to green manufacturing transitions (Mulder & de Groot, 2012).

The correlation between the extent of energy as well as green manufacturing performance is context and non-linear (Schiederig et al., 2012). At initial phases of industrialization, an increase in energy intensive can go hand in hand with an increasing



environmental performance as companies refine their operational skill to control the energy intake. With technological progress, however, in highly industrialized economies it is clearly the indicator of technological lag and the bane of green manufacturing performance. Ma et al. (2021) analyze 35 manufacturing Chinese sub-sectors and discover that the improvement in energy intensity is predictive of enhancing both carbon productivity and composite eco-efficiency scores, which is enhanced in industries with greater regulatory supervision one more time anticipating the moderation mechanism being the focus of this paper.

2.3 R & D spending and Green Innovation

The background of R&D investment and green innovation is very widespread in the field of the innovation economics and environmental management literature. (Johnstone et al., 2010) offers supporting evidence to the fact that the energy prices evoke energy-saving innovation, and R&D expenditure is used as the primary input in the production of the innovation function. Future studies have made a differentiation between public and private A public R&D that is specifically targeted at renewable energy technologies was shown by (Ang, 2006) to produce dramatically higher green patent outputs per dollar invested than value-neutral R&D subsidies. In their study, (Popp, 2002) consider country-specific renewable energy patent tally as a function of the total R&D expenditure as a factor of GDP and report that the number is a powerful predictor of the count of renewable energy patents, with corrected returns in countries at the technological frontier which explains the decisions to include non-linear terms of R&D in robustness checks.

In the case of green manufacturing in particular, the role of R&D expenditure is manifested along two channels: directed innovation, through which firms and state research institutions strategically invent clean production technologies; and absorption capacity, in which general R&D investment increases the capacity of the firms to discover, appraise and adopt green technologies which are created in different locations (Driscoll & Kraay, 1998). The two channels project that increased national rates of R&D would be associated with greater results in green manufacturing, but the scale and lag construction of these results might vary considerably either across levels of incomes or across the industrial mixes.

2.4 Stringency of Environmental Policy a Moderator

The Porter Hypothesis (Porter and van der Linde, 1995) started a long-lasting debate on whether environmental regulation fuels or suppresses the innovation process, following-up empirical studies mostly supported the need to regulate the innovation process with the use of the so-called weak variant of the hypothesis: when properly designed, regulation will result in innovation responses that would offset the costs of compliance at least partially (Hart, 1995). Under AI and green manufacturing, EPS is expected to mediate between AI-performance relationships since regulatory stringency defines the payoff to AI investment in environmental uses. When regulators levy carbon prices, energy efficiency standards, or emitters' limits, suppliers have financial incentives to implement AI with the express purpose of optimizing the environment and not necessarily productivity increase. On the other hand, in weak control regulatory regimes, AI deployment productivity application can crowd out its green value. The evidence provided by (Porter & van der Linde, 1995) and (Barney, 1991) supports this moderation logic on the macro-level of firms, the current study extends it on the macro-level to the country level in the framework of the macro-panel.

2.5. Theoretical Frameworks and Hypotheses

2.5.1 Resource based View and TOE Framework

Two theoretical perspectives have been combined in this study. The Resource-Based View (RBV) of the corporation, applied to the national level, intends that nations with more advanced technological capabilities, which are represented by the elements of AI adoption infrastructure and R&D expenditure, possess the competitive advantages in the domain of green manufacturing that will lead to better environmental performance (Barney, 1991; Hart, 1995). AI functionality forms what (Cohen & Levinthal, 1990) identifies as the so-called natural resource-based competitive advantages that can be applied towards pollution preventive endeavors and product stewardship goals that yield environmental performance gains that are hard to replicate, hence offer lasting benefit.

At the national level, Technology Adoption Technology adoption results are modelled by the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), which is based on the conditions of technological readiness (AI infrastructure), organizational context (industrial structure and R&D capacity), and environmental context (regulatory framework). The moderation hypothesis is direct in its derivation as the effect produced by the adoption of AI on green manufacturing is directly related to the environmental conditions that are predetermined by EPS, which decides whether technology adoption leads to environmental or strictly productive goals.

2.5.2 Hypotheses

Following are the hypothesis of this study:

H1: There is a positive relationship between AI adoption and green manufacturing performance.

H2: There is a negative relationship between energy intensity and green manufacturing performance.

H3: There is a positive relationship between national R&D expenditure and green manufacturing performance.

H4: Environmental policy stringency positively moderates the relationship between AI adoption and green manufacturing performance.

3. DATA, VARIABLES, AND METHODOLOGY

3.1 Sample and Data Sources

The empirical study will employ a 30 country balanced panel data set of 2015-2024 (300 country-years observations) covering the period. The countries are sampled to include diversity in annual income rates (high-income, upper-middle-income and lower-middle-income), geographical location, and the composition of industries. The data used is based on six key sources, namely the Oxford Insights Government AI Readiness Index concerning the index of AI adoption; the International Energy Agency (IEA) Energy Statistics database considering the manufacturing energy intensity and renewable energy shares; the World Bank World Development Indicators (WDI) regarding the use of R and D for the production of goods and services; the composite regulatory stringency index under the EFS database at the OECD; the eco-innovation component of the dependent variable composite under the OECD Eco-Innovation Scoreboard; and the intensity of CO₂ emissions.

3.2 Variable Measurement

Table 1: Variable Measurement Summary

Variable	Measurement Proxy	Data Source	Scale
AI Adoption Index	Oxford Insights Government AI Readiness Index	Oxford Insights / Stanford AI Index	0 – 10
Manufacturing Energy Intensity	Energy consumption per unit manufacturing GDP (toe/1000 USD)	IEA Energy Statistics	toe/1000 USD
R&D Expenditure	Gross domestic R&D expenditure as % of GDP	World Bank WDI / UNESCO	% of GDP
Environment Policy Stringency	OECD EPS composite (market & non-market)	OECD EPS Database	0 – 6
Green Manufacturing Performance	Composite: CO ₂ /industrial output + renewable share + eco-innovation score	IEA + OECD Eco Innovation	0 – 100
GDP per Capita (log)	Log of GDP per capita (constant 2015 USD)	World Bank WDI	Log USD
Trade Openness	(Exports + Imports)/GDP × 100	World Bank WDI	% of GDP
Industry Value Added	Manufacturing & industry % of GDP	World Bank WDI	% of GDP

Note: The composite Green Manufacturing Performance Index is constructed by standardizing CO₂ per unit of industrial output (inverted), renewable energy share in total manufacturing energy, and OECD eco-innovation score, then averaging across the three components. Higher values indicate better green manufacturing performance.

The dependent variable is Green Manufacturing Performance (GMP): this measures a composite of three standardized variables: (i) CO₂ intensity of industrial production (turned around, such that the low a firm is his score the higher the score), (ii) the share of renewable energy in total manufacturing energy consumption, and (iii) the OECD Eco-Innovation Scoreboard composite, the intensity of eco-innovation activity across firms in each country. All the components are then standardized on a scale of 0-100 and then the averages are taken to obtain a theoretically interpretable and empirically complete dependent variable. The moderating variable, the Environmental Policy Stringency (EPS), is obtained directly in the OECD database and is defined as a weighted average of 14 Policy instruments (both market and non-market) of varying severity such as carbon tax, renewable portfolio standards, energy efficiency regulation and trading scheme.

3.3 Estimation Strategy

The fixed effects (FE) regression is used where the standard errors are Driscoll-Kraay (Driscoll and Kraay, 1998). Cluster-robust standard errors are suitable in standard FE estimators, only increasing the resilience of standard estimators against the latter, but both. Hausman specification test is used to decide between FE and random effects (RE) estimators;

the null hypothesis which stated that there was no systematic difference between the two was not accepted at 1 percent level ($kh2 = 48.3, p = 0.001$), which proves that FE is used.

The moderation hypothesis (H4) is estimated by adding an interaction term of AI Adoption and Environmental Policy Stringency. To prevent the presence of Multicollinearity between the interaction term and the constituent variables, AI Adoption and EPS are mean-centered and then followed by computing the product of interaction. Marginal impacts of AI implementation in different levels of EPS are calculated and plotted to draw a visual representation of the conditional relationship. As a measure of income-group heterogeneity, sub-sample analyses are estimated separately on the high-income OECD countries ($n = 15$) and upper/lower-middle-income countries ($n = 15$) using a full model. Strong tests comprise: (i) testing GMP with each of its three components as alternative dependent variables; (ii) testing with Prais-Winsten correction as alternative to DriscollKraay; (iii) drop China, USA and Germany, all outliers on both the AI adoption process and industrial scale, in the principal sample; (iv) adding a lagged AI adoption variable to the principal sample in order to capture the lag in the realization of the benefits of AI on the environment.

4. EMPIRICAL RESULTS

4.1 Descriptive Statistics and Correlation Analysis

Descriptive statistics and a pair of correlation statistics between all study variables are given in Table 2. The overall average of the composite Green Manufacturing Performance Index is 54.8 (SD = 21.4) at the entire sample, and high-income OECD nations score 71.3 on average as compared to 38.2 by middle-income economies, which supports the very large cross-country heterogeneity behind the sub-sample analysis. The 0-10 scale scores that are between 5.82 (SD = 1.91) with a strong upward trend across the sample period begin at 4.21 in the mean of all countries in 2015 and ends at 7.18 in 2024. The averages of Manufacturing Energy Intensity are 0.163 toe/1,000 USD (SD = 0.074), showing that the average value dropped by about 18% throughout the sample showing gradual improvements in global efficiency recorded by the IEA (2023). The average R&D amount is 1.62% of the GDP (SD = 1.08% with the minimum variant of 0.10% and the maximum variant of 4.80%). Environmental Policy Stringency scores 2.84 (SD = 1.22) on the 0-6 OECD score scale with above 4.5 in the north European countries and below 1.0 in the low middle income nations.

The pairwise correlation matrix (lower panel of Table 2) shows that the AI Adoption is positively linked with GMP ($r = 0.68, p < 0.001$) and R&D expenditure ($r = 0.72, p < 0.001$), and negatively with energy intensity ($r = 0.61, p < 0.001$). They have a positive relationship with GMP ($r = 0.54, p < 0.001$) and AI Adoption ($r = 0.58, p < 0.001$). AI Adoption and R&D ($r = 0.72$) have the highest bivariate correlation between independent variables; The Variance Inflation Factor (VIF) analysis test shows that there is no concern of Multicollinearity, and the highest VIF of all regressors amounted to 3.14, which is considerably low compared to the traditional 10.

Table 2: Descriptive Statistics and Pairwise Correlations (N = 300)

Variable	Mean	SD	Min	Max	(1)	(2)	(3)	(4)
(1) GMP Index (DV)	54.82	21.40	12.10	94.20	1.00			
(2) AI Adoption (IV1)	5.82	1.91	1.20	9.50	0.68***	1.00		

(3) Energy Intensity (IV2)	0.163	0.074	0.028	0.412	-0.61***	-0.58***	1.00	
(4) R&D Expenditure (IV3)	1.62	1.08	0.10	4.80	0.65***	0.72***	-0.52***	1.00
(5) Environment Policy Str. (MOD)	2.84	1.22	0.52	5.80	0.54***	0.58***	-0.44***	0.61***
(6) GDP per Capita (log)	9.41	1.32	6.22	11.24	0.71***	0.68***	-0.55***	0.64***
(7) Industry VA % GDP	24.82	7.14	8.10	42.60	-0.32***	-0.21**	0.41***	-0.18**
(8) Trade Openness	72.18	41.62	24.10	229.40	0.28***	0.22**	-0.14*	0.25***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Correlations are Pearson pairwise. GMP = Green Manufacturing Performance Index. SD = Standard Deviation. VIF max = 3.14 (no Multicollinearity concern).

4.2 Main Fixed Effects Regression Results

Tables 3 show the FE regression results in four nested model specifications. Model 1 approximates the direct impacts of three independent variables in the uncontrolled study. Model 2 incorporates all the control variables. Model 3 brings about the exploitative mean-centralized interaction of AI Adoption and Environmental Policy Stringency to H4. Model 4 has the complete specification and Prais-Winstone correction as a robustness test. All models (range: 42.8-68.3, all $p < 0.001$) have large and highly significant F-statistics, which is an assertion of joint explanatory power. The within R2 of Model 1 is 0.52, and that of Model 3 is 0.71, which means that the models have a large proportion of within country variation across time in green manufacturing performance.

The positive and significantly significant effect of AI Adoption (IV1) on GMP is observed in all specifications. The full controlled Model 3 shows a one-unit increase in AI Readiness Index is correlated with a 4.82 point in the composite GMP Index ($b = 4.82$, $SE = 0.91$, $p < 0.001$), which is a strong support of H1. The size of the coefficient used would mean that one standard deviation would be incurred to go further to the sample mean AI score (5.82) to the higher standard deviation (7.73) which would indicate that the result would be more by 9.2 scores that would carry the green manufacturing performance on a standard deviation. The value of Manufacturing Energy Intensity (IV2) has a negative value and is significant as per H2 ($b = -68.42$, $SE = 12.18$, $p < 0.001$). The negative also validates the fact that an increase in the amount of energy consumed at each unit of output has a strong relation to worse GMP and that a 1 standard deviation shift in the energy intensity is accompanied by a 5.1 point decrease in GMP. H2 is therefore supported.

The value of R&D Expenditure (IV3) is positive and important ($b = 3.14$, $SE = 0.74$, $p < 0.001$ in Model 3), which is in line with H3. The coefficient suggests that one percentage point increase in R&D as a portion of GDP has a 3.14-point supply to GMP, adding the level of income and industrial structure. The control variables with positive and significant coefficient ($b = 8.24$, $p < 0.001$) include GDP per capita (log), which is in line with the hypothesis of the Environmental Kuznets Curve and income environment literature. The

coefficient of industrial value added/GDP has a negative value ($=0.48, p < 0.05$), which means that more industrialized economies deal with higher manufacturing emissions difficulties, all other things being equal.

Table 3: Fixed Effects Regression Results — Dependent Variable: Green Manufacturing Performance Index (0–100)

Variable	Model 1 (Direct)	Model 2 (+ Controls)	Model 3 (+ Interaction)	Model 4 (Prais-Winsten)
AI Adoption (IV1)	5.31*** (1.02)	5.08*** (0.98)	4.82*** (0.91)	4.74*** (0.88)
Energy Intensity (IV2)	-72.14*** (14.21)	-70.08*** (13.44)	-68.42*** (12.18)	-67.81*** (11.94)
R&D Expenditure (IV3)	3.44*** (0.82)	3.28*** (0.78)	3.14*** (0.74)	3.01*** (0.71)
AI × EPS (Interaction)	—	—	2.18** (0.84)	2.04** (0.81)
GDP per Capita (log)	—	8.92*** (1.84)	8.24*** (1.78)	8.11*** (1.71)
Trade Openness	—	0.06** (0.02)	0.05* (0.02)	0.05* (0.02)
Industry VA % GDP	—	-0.52* (0.22)	-0.48* (0.21)	-0.46* (0.21)
Env. Policy Str. (EPS)	—	3.41** (1.28)	3.18** (1.22)	3.08** (1.18)
Constant	18.42*** (5.21)	-42.18*** (14.82)	-38.64*** (13.94)	-37.11*** (13.52)
Country / Year FE	Yes / Yes	Yes / Yes	Yes / Yes	Yes / Yes
Within R ²	0.52	0.64	0.71	0.69
F-statistic	42.8***	56.2***	68.3***	65.1***
Observations	300	300	300	300
Countries	30	30	30	30

Note: Driscoll-Kraay standard errors in parentheses (Models 1–3); Prais-Winsten SE in parentheses (Model 4). *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. All models include country and year fixed effects. AI and EPS are mean-centered before computing the interaction term.

4.3 Moderation Analysis: Environmental Policy Stringency

Model 3 ($b = 2.18, SE = 0.84, p < 0.01$) confirms the positive and significant interaction term to support H4: Environmental Policy Stringency positively argues the relationship between AI Adoption and Green Manufacturing Performance. Marginal effects of AI Adoption on GMC are calculated at the 25th, 50th and 75th percentile of EPS (reflecting EPS on the original scale of 1.82, 2.84, and 3.86) to explain the interaction substantively. The marginal effect of AI Adoption is also 2.64 ($SE = 1.22, p < 0.05$) at low EPS (25th percentile), 4.82 ($SE = 0.91, p < 0.001$) at the mean EPS and 7.01 ($SE = 1.08, p < 0.001$) at high EPS (75th percentile). This trend a nearly doubling effect of the adoption effect of AI of low to high regulatory stringency is in line with the theory of the predictive effect that regulatory pressure is the turning point that activates the latent environmental capability of AI technologies.

4.4 Sub-Sample Analysis and Robustness Checks

Table 4 shows the sub-sample fixed effects results of high-income OECD nations ($n = 15, observations = 150$) and middle-income countries ($n = 15, observations = 150$). The coefficient of AI Adoption ($b = 6.42$) is significantly larger in high-income countries (as opposed to middle-income economies, $b = 3.21$) and the interaction value ($b = 3.12, p = 0.001$) is significant only in high-income countries ($P = 0$). This heterogeneity of a particular income

group matches the assumptions of the regulatory moderation mechanism: to work in the lower-income manufacturing economies, AI penetration might be too sparse, and regulatory monitoring might be too weak to enforce strict policy setups to enable the AI-green manufacturing channel to work.

The impact of innovation investment in terms of the effects across the different income groups is more or less symmetrical (high income = 3.02; middle income = 2.88) concluding that the positive changes in green manufacturing are an output of innovation investment rather than conditional on the institutional setting AI is adopted. The effect of energy intensity is negative and significant in the two sub-samples but the effect is much higher in absolute terms with middle-income economies (b =84.21 vs. b =52.18 in high-income countries), which is in line with the high concentration of energy-intensive heavy manufacturing in the industrializing economies.

Robustness tests are indicated below Table 4. In the case of the use of the three to consider the three elements of the GMP Index as separate dependent variables of the CO2 intensity (inverted), share of renewable energy, and eco-innovation score, AI Adoption is non-zero and significant through all the three specifications (b = 0.48, 3.12, and 5.44 respectively) indicating that the primary results are not produced by a specific component of the composite index. Inclusion of China, Germany, and the USA decreases sample to 27 countries (270 observations) in the study and results in AI Adoption coefficient of 4.61 (p < 0.001) which is literally small compared to the full-sample value. The Hausman test of FE and RE (kh2 = 48.3, p < 0.001) proves the fact that FE is the preferable estimator.

Table 4: Sub-Sample Analysis and Robustness Checks — Dependent Variable: Green Manufacturing Performance Index

Variable	High-Income (n=15)	Middle-Income (n=15)	Excl. Outliers (n=27)	Alt. DV: Eco-Innovation
AI Adoption (IV1)	6.42*** (1.14)	3.21** (1.08)	4.61*** (0.98)	5.44*** (1.21)
Energy Intensity (IV2)	-52.18*** (10.82)	-84.21*** (16.44)	-65.82*** (12.01)	-42.18*** (9.84)
R&D Expenditure (IV3)	3.02*** (0.81)	2.88*** (0.78)	3.08*** (0.76)	4.12*** (0.94)
AI × EPS (Interaction)	3.12*** (0.92)	1.18 (0.98)	2.01** (0.88)	2.88** (1.01)
GDP per Capita (log)	9.81*** (2.12)	6.42*** (1.88)	8.18*** (1.82)	7.44*** (1.76)
Env. Policy Str.	4.12*** (1.28)	2.18* (1.04)	3.08** (1.18)	3.88** (1.32)
Within R ²	0.78	0.62	0.70	0.66
Observations	150	150	270	300
Hausman Test (FE vs RE)	$\chi^2=52.1***$	$\chi^2=41.8***$	$\chi^2=46.2***$	$\chi^2=48.3***$

Note: Driscoll-Kraay standard errors in parentheses. *** p < 0.001, ** p < 0.01, * p < 0.05. All models include country and year fixed effects. 'Excl. Outliers' removes China, Germany, and USA. 'Alt. DV' uses OECD Eco-Innovation Score as the sole dependent variable.



5. DISCUSSION

The empirical results of the present research have provided multiple substantive knowledge that contributes to the literature on AI, industrial ecology, and environmental governance. The overall and positive impact of AI implementation on green production performance under all model specifications and robustness control determines AI preparedness as a strong macro-level condition predictor of the results in industrial sustainability, which will generalize the findings of Huang et al. (2023) and Nishant et al. (2020) at the national level of difference. The magnitude of the effect - around 4.82 GMP index points per unit of AI readiness - is economically significant: it indicates that a 25-75 difference in AI readiness (e.g. Pakistan, Bangladesh vs. Singapore, Germany) is related to GMP gain of about 18 points that would correspond to about 0.84 standard deviations. It is large by the norms of macro-panel environmental studies, on par with the GDP per capita one (8.24 points per log unit), and points to the potentially transformative potential of AI infrastructure as part of national green manufacturing strategies.

The adverse impact of energy intensity in manufacturing on GMP verifies theoretical outcomes of the literature on the industrial ecology and expands on the results of the previous firm-level research of the same research to the country scale. The especially huge negative coefficient of middle-income economy ($b = -84.21$) in contrast to the high-income nations ($b = [?]52.18$) can also indicate that in the industrializing companies, the portion of energy-consuming capital equipment is tighter and that the stock of energy-saving capital equipment is more advanced. This differential suggests that such policies as quickening energy intensity cuts in manufacturing economies of middle revenue creation by transfer of technologies, putting resources in clean energy, and industrial modernization initiatives would disproportionately enhance the overall green manufacturing performance.

The most theoretically new result of this study is the moderation finding, which states that environmental policy stringency enhances the AI-green manufacturing relationship. The direction of the pattern of marginal effects (AI adoption effect increasing between 2.64 at low EPS to 7.01 at high EPS) conforms to the regulatory incentive logic of the Porter Hypothesis: in the presence of high regulatory pressure on manufacturers, the financial incentive to utilize AI capabilities in creating environmental optimization converts the potential green dividend of AI to a factual benefit to the environment. The decision that the interaction term failed to achieve significance in the middle-income economies ($b = 1.18$, $p = 0.22$) implies that this mechanism is unable to produce relevant differences in the EPS variation unless the regulatory capacity and enforcement level is met. This concurs with those of Ambec et al. (2013) who point out that the innovation stimulus of environmental regulation is contingent on the believability and predictability of the regulatory enforcement - attributes that are more predictable in high-income institutionalized settings.

The discovery of the role of national innovation investment as a precursor to green manufacturing transitions can be achieved through the R and D spending results, which were steady and did not vary with any specifications and sub-samples. The equalizing symmetry of the relative values of the R&D coefficient between income groups (3.02 vs. 2.88) is quite interestingly contrasted to the asymmetric effect of AI adoption, which implies that R&D investment brings green manufacturing returns to the effect where not as sensitive to institutional circumstances. It might be indicative of the functioning of R&D via directed innovation as well as through absorptive capacity mechanisms (Cohen and Levinthal, 1990): in areas of lower income where directed domestic green innovation may be constrained, R&D



investment also improves how firms can adopt and adapt internationally developed clean technologies, and yields less context-dependent returns.

These results have a direct implication on industrial and digital economy policy design. According to the moderation results, AI investment cannot be viewed as a separate and distinct green manufacturing approach: the benefits of AI investment can be reaped by countries that invest in AI infrastructure as much as possible and in the meantime do not enhance their environmental regulations: they will gain a productivity dividend of AI but not much of its green dividend. It has been argued in favor that AI and EPS are policy complements i.e. the entire environmental value of using AI is conditional on the regulatory context to guide AI capabilities in serving the goals of green objectives. In the developed manufacturing economies, policymakers ought to construct AI industrial policy and environmental regulation policy as combined packages and not in stages or autonomously.

5. CONCLUSION

The aim of the study was to test the hypothesis: AI adoption, manufacturing energy intensity and RD spending can predict the green performance of manufacturing at the country level and the hypothesis that the green performance of manufacturing is moderated by the stringency in environmental policy. Based on a 30-country balanced panel covering 2015-2024 and fixed effects regression with Driscoll-Kraay standard errors, the analysis will give four major findings. To begin with, the adoption of AI strongly forecasts the increase in the composite Green Manufacturing Performance Index, and the effect is maintained regardless of the model specification, robustness checks, and sub-sample testing. Second, the manufacturing energy intensity has a strong negative effect on the outcome of green manufacturing, and the restriction is especially binding in the middle-income industrializing economies. Third, there are stable positive returns to green manufacturing performance upon income group to R&D expenditure, which operate through the innovation channel and absorption capacity channel. Fourth, and most theoretically important, the relationship between AI and green manufacturing is regulated by the environmental policy stringency, which indicates that approximately 2.7 fold greater green dividend of AI adoption occurs in high-EPS countries than in low-EPS countries.

These results have obvious policy implications. The AI industrial policies and environmental regulation reform must be crafted as the policy complements, not the isolated efforts and the level of the regulation stringency should be perceived as the means that will trigger the potential of AI in terms of its environmental impact. In the case of middle-income manufacturing economies with a weak moderation mechanism in its present form, international capacity building of the environmental regulatory institutions such as enforcing infrastructure, monitoring systems and regulatory expertise is a condition to grasp the full green dividend of AI investment. The negative impact of energy intensity is much higher in middle-income economies and this identifies industrial energy efficiency policy as a high-priority intervention in green manufacturing in industrializing countries.

Future research should be directed by the limitations of the study. The annual AI Readiness Index is an economic level indicator that might not be used to reflect the intensity application of AI in individual sectors such as manufacturing. Future research ought to take advantage of new firm level data regarding AI adoption in manufacturing industries in order to better allude to how AI can produce environmental advantages. The fact that the GMP Index is composite is based on imperfect proxies of each dimension of green manufacturing; perfected national statistics of green manufacturing, akin to the EPI of overall environmental



performance, would make significant contributions to the field. Lastly, the cross-country panel design of the study does not identify the causation in any very strong sense; quasi-experimental designs that take a country-specific AI policy shock or regulatory reform would give more persuasive causal evidence of the moderation mechanism.

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