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The Role of Artificial Intelligence in Sustainable Transportation and Manufacturing: Empirical Findings From Southeast Asian Countries

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ABSTRACT

Artificial intelligence is said to be able to lessen environmental harm in many sectors. In this regard, the research examines how the transportation and industrial sectors affect carbon emissions in Southeast Asian nations (China, India, Indonesia, Japan, South Korea, and Thailand) as well as how artificial intelligence may mitigate these impacts. According to the STIRPAT model, the novel panel CS-ARDL approach is used in this context to assess an observation period spanning the years 2004–2022. The results demonstrate that carbon emissions are raised by energy use in the transportation and industrial sectors. In terms of moderating impacts, artificial intelligence applications in the transportation sector show beneficial environmental consequences, while their usage in the industrial sector has no discernible impact on emissions levels. In this regard, policy recommendations are presented for governments to require AI-supported production facilities to use clean energy sources instead of fossil fuels.

JEL Classification: R49, Q55, Q57

1 | Introduction

Climate change, which is characterized as long-term changes in temperature, precipitation patterns, and other atmospheric phenomena primarily brought on by human activity—specifically, the burning of fossil fuels, deforestation, and industrial processes—is one of the most urgent problems facing humanity today (Abbass et al. 2022). Ecosystems and biodiversity are under previously unheard-of peril as a result of climate change, because species find it difficult to adjust to their fast-shifting environments (Godde et al. 2021). A worldwide, cooperative effort is needed to combat climate change to lower greenhouse gas emissions, switch to renewable energy, guarantee the efficiency of fossil fuels, and put sustainable behaviors into place. Although fossil fuels are unsustainable and cause serious environmental problems, they are still used extensively in many industries, and fossil fuel consumption is expected to increase over time due to the rapid civil and industrial growth rate (Yang et al. 2021). For these reasons, policy makers have begun to review their energy strategies and energy policies to minimize the negative effects of climate change (Olabi and Abdelkareem 2022). As a matter of fact, within the scope of combating climate change, nations are trying to determine strategies such as increasing fossil energy efficiency and switching to partially or completely renewable energy sources by improving their existing technologies. For example, at the COP28 held in the United Arab Emirates, agreement was reached on issues such as reducing fossil fuel consumption, renewable energy, and a low-carbon future. Additionally, COP28 aims to evaluate efforts to adapt to climate change, improve risk management, and learn from both successful and unsuccessful initiatives (Jiang et al. 2024).

Countries encounter a number of obstacles in their transition to renewable energy, despite the fact that it is essential in the fight against climate change. For instance, it is challenging to offer reliable energy supplies because renewable energy sources are intermittent and subject to the hour of the day and climate (Neacsa et al. 2022). Furthermore, installing renewable energy systems, including infrastructure in the form of solar farms, wind turbines, and transmission lines, is expensive. For the majority of developing countries, despite long-term cost savings, insufficient financial resources present a major energy transition challenge (Adelekan et al. 2024). Again, the fact that most of the existing energy grids in most developing countries are designed for fossil fuel power plants and their dependence on fossil fuel use highlights the need to make fossil fuel efficiency a priority. This dependence is even more pronounced in developing countries, given that fossil fuels are likely to be the primary source of cheap and accessible energy to drive growth. Yet dependence on fossil fuels is normally succeeded by inefficiencies in their consumption, distribution, and extraction. This dependence and inefficiency may prove highly daunting to environmental management as well as sustainable development (Adom and Adams 2020). Less developed countries should try to make sure fossil resources are used as effectively as possible in the fight against climate change because of their usage of fossil fuels and the expense of putting alternative renewable energy sources into place. As of 2021, fossil fuels will make up around 82% of primary energy consumption (ENC), which will greatly contribute to environmental sustainability; hence, it is imperative that they be utilized as sustainably as possible (Li 2024). Additionally, fossil fuel efficiency is an important strategy to increase energy security, reduce costs, and mitigate environmental impacts in developing countries. However, the expected benefits of energy efficiency are usually diminished by the rebound effect, in which efficiency increases lead to increased energy use and negate the expected energy and carbon savings. In other words, the rebound effect may be a result of increased access to energy services and economic development, even while it lessens the immediate benefit of efficiency gains.

Energy is the basis of social progress and economic development; yet, especially in developing countries that are dependent on fossil energy, large-scale uses of fossil energy and a lack of capability to guarantee fossil energy efficiency have led to environmental problems, and under such conditions, countries have initiated advancing to promote energy transformation and sustainable development based on higher energy efficiency. Artificial intelligence (AI) is a key technology that has the potential to accelerate the transformation in the energy industry and drive economic development through energy efficiency. Technology-driven development forms the core of this process (Li et al. 2023). AI has indeed transformed the approach of industries and governments to fossil energy efficiency and offers state-of-the-art instruments for energy system optimization, reduction of losses, and restriction of environmental impacts. AI instruments have been applied more urgently in manufacturing, energy, banking, and other industries since their inception, with various impacts on human life and manufacturing practices (Zavyalova et al. 2023). Furthermore, the pace of advancement in AI is encouraging more and more countries to become fossil energy efficient and to facilitate energy transitions. For example, AI is described to reduce the cost of transport and emissions by reducing supply chain transportation routes and logistics of oil, coal, and gas and helping conserve the environment by integrating fossil fuel production with green resources by forecasting energy demand (Wang et al. 2024). The application of AI to energy policy generally offers groundbreaking ways to optimize energy systems, lessen environmental impacts, and foster economic growth (GRO), particularly in developing nations. It is also a trailblazing factor in boosting the efficiency of fossil fuels and enabling sustainable energy transitions.

By integrating AI into environmental interventions and policies, governments, organizations, and companies can accelerate their advancement toward a sustainable future. Accordingly, AI has lately been increasingly recognized as a promising means for reshaping the causes of environmental degradation (ENVD) and facilitating the achievement of the Sustainable Development Goals (SDGs) (Mondejar et al. 2021). AI plays a role in digital transformation with the possibility of offering advanced tools to guide businesses toward low-carbon systems. CO_2 emission estimation is important for environmental sustainability, and technological development makes the application of efficient solutions possible. It also facilitates carbon footprint estimations, making the adoption of efficient measures possible to improve environmental conditions (Rasheed et al. 2024). AI, a groundbreaking technology in the big data period, greatly improves the gathering of environmental data and enhances the potential for CO_2 emission reduction to the greatest extent. Whereas AI progress may lower emissions via increased energy efficiency and less consumption of fossil fuels, its industrial growth rebound effect can contribute to higher emissions. With developing countries relying on fossil fuels and economically unable to utilize renewable energy, understanding the impacts of AI on emissions and its internal dynamics and spatial heterogeneity is vital (Xu and Song 2023).

Combating global warming and enhancing environmental performance can be helped by the adoption of AI technology in the industrial and transport industries. For example, AI-based technologies can improve efficiency by making intelligent routing possible, predictive maintenance, and smart use of resources in manufacturing operations, maximizing energy use and minimizing CO_2 emissions. These developments are to lower carbon footprints and reduce wastage, consistent with global standards of sustainability (Mao et al. 2019). AI improves efficiency in the transportation system, something that can yield tremendous reductions in CO_2 emissions. Intelligent transport systems using AI, for example, can optimize traffic flow, reducing congestion as well as attendant emissions (Chen et al. 2023). Besides, AI also has an important part to play in the advancement of green technology. By integrating AI with renewable energy resources such as smart grids, transportation can be made more sustainable and energy efficient. AI can regulate the use of energy in electric vehicles and also optimize charging systems, which are essential for reducing the environmental footprint of electric transport (Taherdoost 2023). There can also be significant environmental sustainability implications from the use of AI in the industrial world. Industries in the last several years have shifted toward sustainable manufacturing under pressure from consumers, governments, and social organizations (Agrawal et al. 2023). Through compromises among environmental, social, and economic objectives, these AI-enabled manufacturing processes try to attain maximum use of resources, minimum emissions, and quality of life (Liu et al. 2022). Furthermore, AI integration into the manufacturing process can foster production efficiency by optimizing the supply chain via enhanced inventory levels, lower lead times, and greater product availability (Adenekan et al. 2024). AI can also minimize defects and waste by using real-time quality monitoring systems that can detect manufacturing complexity and enable instant corrective actions (Plathottam et al. 2023).

Gaining from AI and robotics is expanding rapidly in Southeast Asian countries, driven by technological advancements and the region's focus on maximizing industrial efficiency and competitiveness, and many countries in the region are embracing AI and robotics in various sectors, including manufacturing, logistics, healthcare, and agriculture. For instance, Malaysia and Indonesia are set to adopt Singapore's National Artificial Intelligence Strategy, unveiled in 2019. Thailand, a regional leader in industrial robots with approximately 3000 units in operation in 2019, has integrated AI into its National Development Plan and has focused on AI, robotics, and digital industries through its Thailand 4.0 policy (Mongkol 2023). In 2021, Vietnam, a Southeast Asian nation, established its first national AI strategy for research, development, and application, detailing plans through 2030 and showcasing a strong commitment to advancing AI technology. Vietnam has actively sought assistance from Australia in the development and application of AI technologies (Pham et al. 2024). Once again, the AI market in Japan is expected to expand by 23.51% between 2015 and 2030. The biggest AI subsegment in Japan is the wholesale and retail sector, which accounts for 39% of the market value (Rosales et al. 2020).

The purpose of this research is to examine how the transportation and industrial sectors affect carbon emissions, as well as how AI may mitigate these impacts for Southeast Asian nations, based on the topics above. The findings demonstrate that carbon emissions are raised by energy usage in the industrial and transportation sectors. AI applications in the transportation sector have positive environmental effects from a mitigation standpoint, while their usage in the industrial sector has no appreciable effect on emissions. It is anticipated that this study will add to the body of literature. (i) The research is the first to look at how the transportation and industrial sectors affect the environment in Southeast Asian nations. (ii) For the first time in literature, the moderating effects of AI use in different sectors are investigated. (iii) Relying on the STIRPAT environmental model while creating empirical models makes the empirical findings more reliable. (iv) Utilizing techniques that consider cross-sectional dependency (CSD) in panel data analyses allows us to take into account the shock permeability among the observed countries. (v) AMG technique is used to check the robustness of the findings.

2 | Literature Review

While industrial activities support GRO, they also contribute significantly to ENVD, including pollution, resource depletion, and climate change. This relationship between industrialization (IND) and the environment highlights the dual challenge of pursuing industrial progress while reducing its ecological impacts. Shahbaz et al. (2014) studied the effects of ENC and IND on ENVD in Bangladesh for the period 1975–2010 and the findings of the study showed that the EKC hypothesis is valid between IND and ENVD. In another study, Li and Lin (2015) investigated the effects of IND, ENC, and urbanization (UBN) on ENVD in low, middle, and high-income countries for the period 1971–2010. According to the empirical findings of the study, IND reduces ENC but increases ENVD in all income group countries. When recent studies are examined, Munir and Ameer (2020) analyzed the long-term and short-term nonlinear effects of GRO and IND on ENVD in Pakistan for the period 1975–2016 and concluded that the increase in IND has a positive and significant effect on ENVD, while the decrease in IND has a negative and insignificant effect on ENVD. In another study, Opoku and Aluko (2021) investigated the environmental impact of IND with a quantile regression model on data from 37 African countries (2000–2016). The findings reveal that IND increases ENVD in the lower quantiles (10–30) but decreases it in the upper quantiles (40–90).

Despite having some of the world's fastest-growing economies, Southeast Asia is also very susceptible to climate change and environmental deterioration. Therefore, the relationship between IND and ENVD has become a critical area of concern, especially in rapidly developing regions like Southeast Asia. Sumaira and Siddique (2023) studied the environmental impacts of IND, UBN, and ENC in Southeast Asian countries during the period 1984–2016, and the empirical results show that IND and ENC are important indicators of ENVD. Ahmed et al. (2022) studied the impact of IND and foreign direct investment (FDI) on ENVD in 55 Asia-Pacific countries (1995–2020). The findings reveal that FDI significantly increases ENVD by increasing methane and CO_2 emissions, while IND has a moderate positive impact on the environment. Finally, Siddique (2021) investigates the effects of IND and trade openness on ENVD in South Asian countries for the period 1990–2018, considering the roles of capital and UBN. The findings show that IND, trade openness, and UBN contribute to ENVD, while renewable ENC helps reduce it.

The relationship between transportation and ENVD is a vital issue, especially in the quest for sustainable development. Transportation systems play a key role in environmental sustainability as they contribute greatly to greenhouse gas emissions, air pollution, and depletion of natural resources. Exploring this linkage is crucial for formulating policies and strategies that minimize environmental damage while advancing sustainable transportation practices. Shafique et al. (2021) examine the relationship between transportation, GRO, and ENVD for the 10 Asian economies with the highest CO_2 emissions during the period 1995–2017. Using panel pooled means ensemble and ARDL models, the study identifies long-run linkages among the variables. The Dumitrescu and Hurlin causality test reveals unidirectional causality running from transportation to GRO and from transportation to ENVD. Furthermore, the findings highlight that there is an endogenous relationship between transportation, GRO, and ENVD and that GRO and the transportation sector are the main drivers of ENVD. Umar et al. (2021) examined the impact of biomass and fossil fuel ENC on transportation-related CO_2 emissions and found that fossil fuel energy use in transportation significantly increased ENVD. In another study, Liu et al. (2023) examined the relationship between transportation, GRO, and ENVD in China (1995–2018) using the QARDL approach. The findings show mixed results: Freight transportation only improves environmental quality at the upper end quantiles and has no significant impact in the short term, while passenger transportation reduces ENVD at the lower quantiles in the long run, while showing significant impacts at the upper quantiles in the short run. In another study for China, Hassan et al. (2021) analyzed the most sensitive transportation system in China via the NARDL method using data covering the period 1985–2018, and the findings revealed that both positive and negative transportation shocks affect ENVD in China by reducing the per capita operational distance of air, road, and waterways. Nasreen et al. (2020) investigate the long-run relationship between GRO, transportation ENC, and ENVD for 18 Asian countries by considering structural breaks and cross-sectional dependencies. The long-run elasticities estimated through CMG show that a 1% increase in transportation ENC and GRO deteriorates environmental quality by 0.57% and 0.46%, respectively. The findings highlight the need for energy-efficient technologies in the transportation sector to support GRO while preserving environmental quality. Finally, Batool et al. (2023) examine the role of ICT in reducing ENVD through transportation ENC and UBN in Asian countries. The findings confirm the Environmental Kuznets Curve (EKC) hypothesis, which shows that ENVD decreases when ICT exceeds a threshold level due to the higher scale effects of technological advances in ICT. Furthermore, the findings highlight the potential of ICT to improve environmental quality and provide policy recommendations for sustainable transportation and urban development.

As the impacts of climate change, biodiversity loss, and resource depletion intensify, innovative solutions are needed to mitigate these problems and promote sustainable development. From optimizing energy efficiency to reducing ENVD and improving natural resource management, AI-driven solutions have the potential to create a more sustainable future. Recent studies (Rolnick et al. 2022; Xie et al. 2022; Chen et al. 2023) have shown that AI technologies have the potential to play a significant role in reducing ENVD and achieving carbon neutrality. Additionally, many studies (Diao et al. 2021; Waltersmann et al. 2021; Fang et al. 2023) have shown the positive impact of AI on reducing ENVD in many sectors, including manufacturing, energy systems, and waste management. As Southeast Asia is one of the most vulnerable regions to the impacts of climate change, facing rising sea levels, extreme weather events, and significant threats to agriculture and biodiversity, AI technologies offer tremendous potential to address these challenges by providing innovative and effective solutions, but there is still a lack of sufficient studies in this area. Zhong et al. (2024) investigated whether AI can contribute to a synergistic reduction in ENVD in China, the largest carbon emitter on a global scale, for the period 2006–2019, and empirical findings show that AI plays an important role in synergistically reducing ENVD by promoting technological advances and improving industrial structures. In another study for China, Ding et al. (2023) suggested that AI development effectively contributes to the reduction of ENVD, and the reduction effect remains consistent across spatial weights. Ahuja and Mehra (2023) examined the effects of AI use in the Indian agricultural sector on ENVD from agriculture and concluded that the use of AI-based applications in agriculture would significantly reduce ENVD in India by 2030. Finally, Akhtar et al. (2024) investigated the interaction between industrial robots, digital economy, ENC, green energy technology, industrial structure, and GRO in the context of ENVD in South Korea for the period 2010–2019. The findings of the study show that industrial robots and green energy technologies can reduce ENVD and support environmental sustainability.

3 | Empirical Procedure

3.1 | Model and Data

To observe the environmental impacts of human development, the IPAT model developed by Ehrlich and Holdren (1971) is generally used as a basis in environmental economics literature. Here, I, P, A, and T denote environmental impact, population, affluence, and technology, respectively. Later, for this model to explain causal relationships, Dietz and Rosa (1997) transformed this model into a stochastic version and transformed it into the STIRPAT (Stochastic impacts on the environment by regression on population, affluence and technology) model. Using the expanded STIRPAT model with sectors and panel data, we develop two distinct basic models in this study:

$$co_{it} = a_0 + a_1 gdp_{it} + a_2 urb_{it} + a_3 ei_{it} + a_4 man_{it} + a_5 ai_{it} + \varepsilon_{1it} \quad (1)$$

$$co_{it} = \beta_0 + \beta_1 gdp_{it} + \beta_2 urb_{it} + \beta_3 ei_{it} + \beta_4 tra_{it} + \beta_5 ai_{it} + \varepsilon_{2it} \quad (2)$$

where carbon emission (*co*) is used to represent environmental impact, real national income (*gdp*) to represent affluence, urban population (*urb*) to represent population, and energy intensity (*ei*) and AI use (*ai*) to represent technology. In the context of the environmental impacts of sectors, manufacturing industry (*man*) and transportation (*tra*) indicators are used. Throughout the research, Equation (1) is referred to as Model I, and Equation (2) as Model II. In accordance with the main purpose of the study, the following models are created to see the moderating roles of AI on the environmental impacts of sectoral developments:

$$\begin{aligned} co_{it} = \theta_0 + \theta_1 gdp_{it} + \theta_2 urb_{it} + \theta_3 ei_{it} + \theta_4 man_{it} \\ + \theta_5 ai_{it} + \theta_6 ai * man_{it} + \varepsilon_{3it} \end{aligned} \quad (3)$$

$$\begin{aligned} co_{it} = \gamma_0 + \gamma_1 gdp_{it} + \gamma_2 urb_{it} + \gamma_3 ei_{it} + \gamma_4 tra_{it} \\ + \gamma_5 ai_{it} + \gamma_6 ai * tra_{it} + \varepsilon_{4it} \end{aligned} \quad (4)$$

where Equation (3) refers to Model III, and the term "$ai * man$" in this model refers to the interaction between AI and manufacturing. In other words, the environmental effects of AI use in the manufacturing sector are being investigated. In addition, the environmental effects of AI use in the transportation sector are being investigated with the indicator "$ai * tra$" in Equation (4), which refers to Model IV.

In the study, all variables are included in the analysis in natural logarithmic form. In this process, due to data limitations, the annual data of 2004–2022 is used as the observation period. When selecting Southeast Asian countries, China, India, Indonesia, Japan, S. Korea, and Thailand, whose data can be accessed, are considered. Per capita metric ton carbon emission (*co*) represents ENVD, real GDP in dollars per capita represents real national income (*gdp*), share of urban population in total population (*urb*) represents UBN, energy intensity level of primary energy (*ei*) represents energy intensity, industry ENC (*man*) represents manufacturing, transport sector ENC (tra) represents transportation, and robotic installations (*ai*) represent AI. While *co*, *gdp*, *urb*, and *ei* data are obtained from the World Development Indicators database, *man* and *tra* data are obtained from the International Energy Agency database. Finally, *ai* data are obtained from the International Federation of Robotics.

3.2 | Methodology

In order to determine the roadmap for the techniques to be selected in empirical analyses, some pretests need to be conducted. In this context, first, the correlation relationship between the variables is determined. The most important issue here is whether there is a high correlation relationship between the independent variables because a high correlation relationship between the regressors indicates a multicollinearity problem. In the next stage, shock dependency between the countries in question is investigated. Indeed, the fact that Southeast Asian countries are economically intertwined with each other and with the global economic system requires considering the effects of these shocks in empirical analyses. In this context, the CD test developed by Pesaran (2004) is used while investigating CSD. Then, the stationarity of the variables is investigated with the CIPS unit root test developed by Pesaran (2007). In the next stage, it is necessary to investigate whether there is any long-term relationship between the variables. In this direction, the validity of the long-term relationship between the variables is investigated with the ECM-based cointegration technique developed by Westerlund (2007). Additionally, the research examined the immediate and long-term impacts on the *co* of regressors using the CS-ARDL approach. Using this method has a number of benefits. First, the capacity to distinguish between short-term and long-term impacts is a major benefit because it is an ARDL-based approach. Additionally, CS-ARDL reduces endogeneity, a key issue in regression estimates, by taking into account interactions between the dependent variable and the lagged values of the regressors. Finally, it allows us to obtain more accurate results by taking into account both fixed effects and random effects models.

The 1-year lag of the regression variable is regarded by the CS-ARDL paradigm as a weak exogenous regressor during the error correction procedure. By using a linear combination of the independent and dependent variables' mean cross sections to account for CSD in the error term, Chudik and Pesaran (2015) assert that the CS-ARDL approach enhances the ARDL model:

$$co_{i,t} = \beta_i + \mu_{ji} \sum_{j=1}^{ay} co_{i,t-j} + \alpha_{ji} \sum_{j=0}^{bx} X_{i,t-j} + \mu_{ji} \sum_{j=0}^{c} \overline{co_{i,t-j}} + \alpha_{ji} \sum_{j=0}^{d} \overline{X_{i,t-j}} + e_{i,t} \tag{5}$$

where *co* is emissions which indicates ENVD and *ay* and *bx* are optimum lag lengths; $X_{i,t}$ is the regressor matrix that combines regressors. In addition, the long-run parameters are computed as follows:

$$\hat{\theta}_{CS-ARDL,i} = \frac{\sum_{j=0}^{bx} \hat{\alpha}_{ji}}{\sum_{j=1}^{ay} \hat{\mu}_{ji}} \tag{6}$$

To introduce the statistical forms of the variables, we use descriptive statistics, as shown in Table 1. These tables show that carbon emissions have the lowest mean value while AI has the greatest mean value. In terms of standard deviation, *ai* exhibits the highest volatile behavior. In addition, *co*, *urb*, and *ai* are skewed to the left, while the other variables are skewed to the right. Finally, *ei* exhibits a leptokurtic distribution, while the other variables exhibit a platykurtic distribution.

The correlation matrix illustrating the link between the variables in the empirical models developed for the research is

TABLE 1 | Descriptive statistics.

	co	*gdp*	*urb*	*ei*	*man*	*tra*	*ai*
Mean	1.511	8.883	4.015	1.616	8.307	7.768	10.457
Median	1.413	8.664	3.966	1.619	8.007	7.642	10.425
Maximum	2.566	10.497	4.521	2.386	10.763	9.578	14.222
Minimum	0.027	6.794	3.364	1.112	6.831	6.594	4.796
Std. dev.	0.799	1.160	0.361	0.292	1.169	0.809	2.107
Skewness	−0.224	0.065	−0.062	0.446	0.927	0.641	−0.367
Kurtosis	1.557	1.713	1.829	3.124	2.654	2.563	2.344
Observations	114	114	114	114	114	114	114

shown in Table 2. As a result, there is a negative correlation between *co* and all variables except *ai*. Furthermore, it can be concluded that multicollinearity is not an issue in any of the models because the correlation between the independent variables is weak for all of them.

4 | Empirical Results

4.1 | Main Results

In the first stage of panel data analysis, shock dependency should be investigated on a variable basis for the countries considered. The result obtained here determines the selection of the tests to be used in the next stages. In this direction, the CSD test results are presented in Table 3. According to the results, the null hypothesis indicating that there is no CSD is strongly rejected for all variables. This result indicates that other countries are also affected by a shock occurring in any of the Southeast Asian countries for any variable. In addition, it is decided that the unit root and cointegration techniques to be used in the next stage should be techniques that do not ignore CSD.

The unit root test that allows CSD and is frequently used in environmental economics literature is the CIPS unit root test. The unit root test results, which investigate the stationarity process of each variable, are presented in Table 4. The result shows that while all variables have unit roots in their level forms, the null hypothesis is rejected in their first difference forms and the stationarity process occurs. An examination of the cointegration connection between the variables in the context of CSD is necessary in light of this conclusion.

Table 5 presents the Westerlund cointegration test results for four different models. Accordingly, for the first model, which is based on the manufacturing sector, Ga, Pt and Pa statistics emphasize the validity of cointegration. In the second model, which is based on the transportation sector, cointegration is valid according to Gt, Ga, and Pa statistics. According to Model III, Ga and Pa statistics; according to Model IV, Gt, Ga, and Pa statistics confirm the long-term relationship.

Following the identification of cointegration across variables, Table 6 presents the separation of the regressors' short-term and long-term environmental impacts using the CS-ARDL approach. The results for Model I, which is based on the manufacturing sector, show that short-term increases in GDP, URB, EI, and MAN lead to higher emissions. AI, on the other hand, lowers the emission level. The variable parameters' signs remain constant throughout time. Model II, which uses the transportation sector as its foundation, yields similar results. It shows that increases in GDP, URB, EI, and TRA raise emissions over the medium and long terms. In this concept, AI also contributes to lower emissions.

The findings for the models in which moderating effects are considered (Model III and Model IV) are also presented in Table 6. According to the findings obtained for Model III, in the short term, the increase in GDP, URB, and EI increases carbon emissions. On the other hand, there is no discernible impact of

TABLE 3 | The results of CSD.

Variables	CD statistics	*p* value
co	7.550***	0.000
gdp	15.950***	0.000
urb	11.100***	0.000
ei	15.200***	0.000
man	7.600***	0.000
tra	5.330***	0.000
ai	10.540***	0.000

Note: *** shows statistical significance at the 1% level.

TABLE 4 | The results of panel unit root.

Variables	Level	1st difference
co	−1.482	−3.638***
gdp	−2.168	−3.312***
urb	−1.546	−3.342***
ei	−1.768	−3.440***
man	−1.728	−4.047***
tra	−1.785	−3.352***
ai	−1.839	−3.346***

Note: Critical values are −2.210, −2.340, and −2.600 at 10%, 5%, and 1% level, respectively. *** indicate statistical significance at 1% level.

TABLE 2 | Correlation matrix.

	co	gdp	urb	ei	man	tra	ai
co	1.000						
gdp	0.941	1.000					
urb	0.857	0.358	1.000				
ei	0.221	−0.095	−0.216	1.000			
man	0.101	−0.130	−0.163	0.541	1.000		
tra	0.195	0.025	0.017	0.331	0.957	1.000	
ai	−0.555	0.812	0.725	0.055	0.334	0.478	1.000

TABLE 5 | The results of panel cointegration.

Statistics	Model I	Model II	Model III	Model IV
Gt	−1.257	−3.090*	−1.772	−3.856**
Ga	−9.172***	−6.245**	−7.583**	−9.491***
Pt	−4.517*	−3.589	−2.636	−3.147
Pa	−4.713*	−7.243**	−7.757**	−14.241***

Note: At the 10%, 5%, and 1% levels, statistical significance is indicated by the symbols *, **, and ***.

TABLE 6 | The results of CS-ARDL estimation.

Variables	Model I Coefficients	Model II Coefficients	Model III Coefficients	Model IV Coefficients
Short-run				
gdp	0.704***	0.732***	0.764***	0.759***
urb	0.598**	0.380**	0.666**	0.645***
ei	0.543***	0.580***	0.490***	0.594***
man	0.223***	—	—	—
tra	—	0.265**	—	—
ai	−0.027**	−0.061**	—	—
*ai*man*	—	—	0.002	—
*ai*tra*	—	—	—	−0.014**
ECT(−1)	−0.771***	−0.710***	−0.882***	−0.985***
Long-run				
gdp	0.386***	0.379***	0.393***	0.480***
urb	0.461***	0.334**	0.388**	0.358***
ei	0.309***	0.525***	0.490***	0.498***
man	0.130***	—	—	—
tra	—	0.080**	—	—
ai	−0.028*	−0.037***	—	—
*ai*man*	—	—	0.001	—
*ai*tra*	—	—	—	−0.006**

Note: At the 10%, 5%, and 1% levels, statistical significance is indicated by the symbols *, **, and ***.

AI on the industrial industry. In the long run, the results are the same, and emissions rise as GDP, URB, and EI rise. AI will not be able to stop the industrial sector's long-term impact on emissions.

The results for Model IV show that gains in *gdp*, *urb*, and ei raise emissions in the near run, indicating the use of AI in the transportation industry. The parameters of the interaction variable between transportation and AI on emissions are negative. The long-term influence of GDP, ei, and *urb* on emission increases remains unchanged. Similar to the short term, the long-term impacts of AI in the transportation industry are effective in reversing the sector's tendency to increase carbon emissions.

4.2 | Robustness Check

The Augmented Mean Group estimator is used at this stage to examine the long-term effects of the variables on *co* in order to verify the validity of the results from the previous step. When all models are considered collectively, the results shown in Table 7 indicate that a 1% rise in *gdp* raises *co* by 0.824%–0.940%, a 1% increase in *urb* raises *co* by 0.437%–0.545%, and a 1% increase in *ei* raises *co* by 0.264%–0.807%. In contrast, in Model I, a 1% increase in *man* results in a 0.192% rise in *co*. AI utilization has a negative coefficient. Likewise, in Model II, a 1% rise in *tra* results in a 0.254% increase in co. This model also demonstrates AI's ability to reduce emissions. The manufacturing industry and AI integrated variable have a statistically negligible parameter. However, the parameter for the integrated variable *ai*tra* is statistically significant and negative.

A brief overview of the empirical analysis's results indicates that UBN, economic expansion, and energy intensity all contribute to short- and long-term increases in carbon emissions as summarized in Figure 1. In a similar vein, the growing economic importance of the industrial and transportation sectors in Southeast Asian nations contributes to both short-term and long-term environmental damage. Regarding the moderating functions of AI, the negative environmental consequences of the industrial sector cannot be eliminated by its use. However, applying AI to the transportation industry has the potential to completely eradicate or even reverse the sector's negative environmental effects.

5 | Discussions

This section discusses potential explanations for the empirical results together with theoretical justifications and realities unique to each nation. First, the EKC theory and its scale impact may be used to assess how economic expansion affects emissions. This theory states that carbon emissions rise with economic expansion at first, but then fall as a result of cleaner technology and more environmental consciousness after income reaches a certain threshold. However, in developing and newly industrialized economies (China, India, Indonesia, Malaysia and Thailand), the scale effect is dominant, meaning that industrial expansion, ENC, and transportation demand lead to higher emissions. In high-income economies such as Japan and Korea, emissions are lower per unit of GDP due to

TABLE 7 | The results of AMG estimation.

	Model I	Model II	Model III	Model IV
Variables	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**
gdp	0.824***	0.904***	0.940***	0.930***
urb	0.437*	0.442*	0.544*	0.545**
ei	0.264***	0.779***	0.627**	0.807**
man	0.192***	—	—	—
tra	—	0.254**	—	—
ai	−0.005**	−0.050**	—	—
*ai*man*	—	—	0.002	—
*ai*tra*	—	—	—	−0.003**

Note: At the 10%, 5%, and 1% levels, statistical significance is indicated by the symbols *, **, and ***.

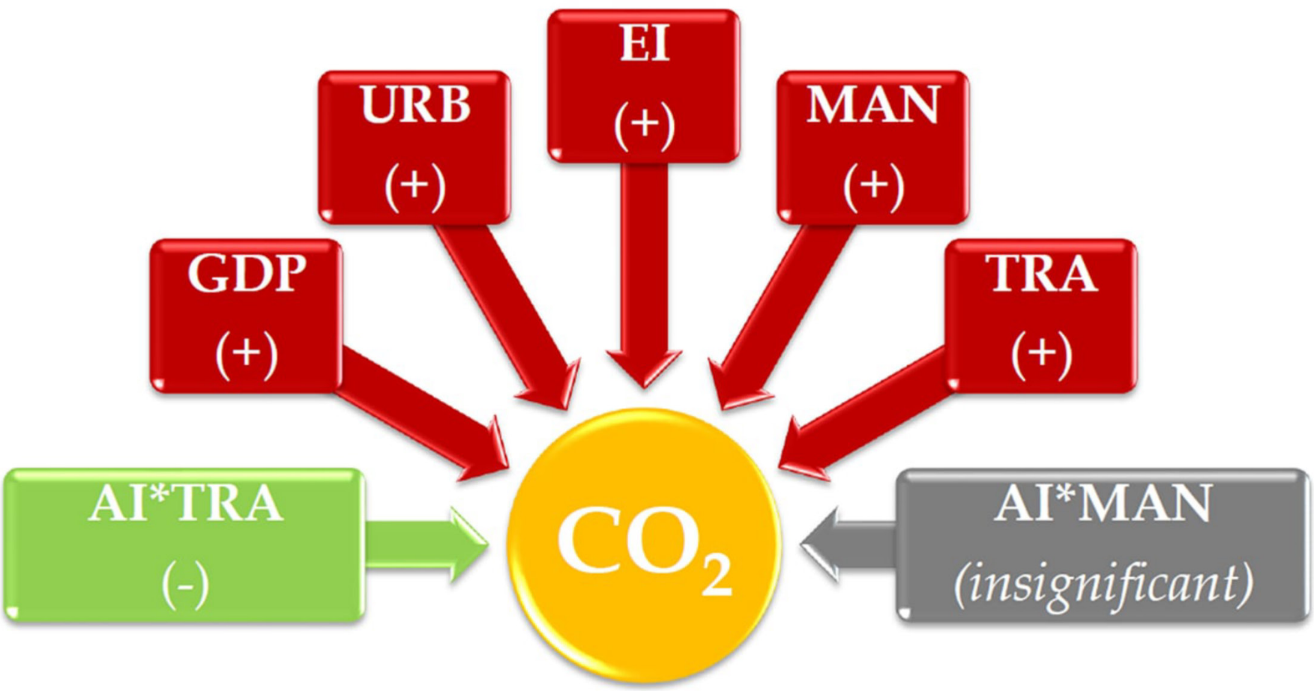

FIGURE 1 | Summary of the empirical results.

energy efficiency, but their industrial sectors still contribute to carbon output.

Regarding the emission-increasing effects of UBN, rapid UBN increases energy demand due to higher electricity consumption, transportation needs, and construction activities. Carbon emissions rise as a result of the urban heat island effect and cities' greater per capita energy use. In many developing countries, urban expansion leads to deforestation, reducing natural carbon sinks. It is also an expected finding that energy intensity increases carbon emissions. Higher energy intensity generally means greater dependence on fossil fuels. Lower energy intensity may indicate higher energy efficiency or a shift toward renewable energy.

Determinations are made regarding the pollution-increasing effect of IND. Production is an energy-intensive sector and generally involves the combustion of coal, oil, and natural gas. How industrial production affects the environment depends on the components of the energy used in production. The main reason for this finding is that China, India, and Indonesia focus on production with coal-based industries. China is also the world's largest industrial economy, with large polluting sectors in steel, cement, and chemicals, which makes this finding an expected finding. Similarly, for India, industrial production contributes more than 20% of GDP, but its dependence on coal makes it a significant source of emissions. In Indonesia and Malaysia, the main industries are energy-intensive sectors such as palm oil, mining, and electronics.

The transportation sector also has a proven effect on carbon emissions. Transportation emissions are primarily driven by vehicle ownership, freight transport, and fuel type. Emissions are higher in countries with poor public transport and high dependence on gasoline vehicles. China has the world's largest automobile market, as well as the rapid motorization of China and India with diesel-based transportation. The high dependence on cars and motorcycles and limited public transportation in Indonesia and Malaysia also contribute to the environmental impacts of the transportation sector.

As for moderating effects, our study finds that AI does not significantly reduce carbon emissions. China, India, and Indonesia have long-established, capital-intensive industries that still rely on traditional, fossil-fuel-fired processes. Firms are locked into existing technologies due to high sunk costs (e.g., steel, cement, and petrochemicals) and are likely reluctant to transition to sustainable AI-driven practices. In Japan and Korea, where AI adoption is high, it may be used primarily to increase efficiency rather than decarbonize production. However, these efficiency gains may lead to higher output and resource utilization. This phenomenon is called the Jevons Paradox (Rebound Effect). For example, AI-enabled automation in China's automobile, electronics, and steel sectors is increasing production capacity, which in turn increases energy demand. Indonesia, Malaysia, and Thailand have lower AI adoption rates due to limited R&D investment, weak digital infrastructure, and insufficient government incentives. The manufacturing sector in these countries remains labor-intensive, relying on low-cost workers rather than AI-powered automation.

On the other hand, our research revealed that AI can reverse or completely eradicate the environmental harm caused by the transportation industry. There are several possible reasons for this. AI-powered intelligent traffic management systems, route optimization, and autonomous vehicles reduce fuel consumption and emissions. China and Korea are global leaders in AI-integrated transportation, using real-time traffic monitoring and AI-powered urban planning to reduce congestion and emissions. Indeed, Japan has significantly reduced transportation emissions by pioneering AI-powered automated rail networks and electric vehicle (EV) innovation. AI has been deeply integrated with EVs (e.g., smart charging, battery optimization) to reduce reliance on gasoline and diesel vehicles. Similarly, AI-powered bus and rail systems for India and Indonesia are improving efficiency in urban areas. China, Japan, and Korea have strong government-led AI and green transportation policies, including subsidies for AI-powered EVs, high-speed trains, and smart traffic systems.

Additionally, lessons can be learned by examining the policies implemented by countries where AI has been successfully and effectively used in these sectors. For example, Diran et al. (2021) found that AI-based traffic management in the Netherlands reduced urban CO_2 emissions by 15%. Similarly, in the industrial sector, Kumar et al. (2024) reported that AI-supported maintenance and optimization in production facilities reduced energy loss by up to 20%.

6 | Concluding Remark

6.1 | Conclusions

There are claims that with the use of AI in sectors such as manufacturing and transportation, carbon emissions from these sectors will decrease significantly. However, the empirical validity of these claims has not been examined by any research. In light of this, the research first looks at how Southeast Asian nations' industrial and transportation sectors directly affect their carbon emissions and then how the effects of these sectors on the environment change with the use of AI. In addition, real GDP, UBN, and energy intensity are included in the model as regressors in order not to cause omitted variable bias. In doing so, the period 2004–2022 is analyzed with second-generation panel data techniques.

The results of panel data estimators indicate that these nations' economic expansion, UBN, and rising energy intensity greatly raise carbon emissions. In addition, the increasing weight of both the manufacturing sector and the transportation sector in the economy leads to an increase in carbon emissions. In the context of the moderating role of AI, no environmental impact of the use of AI in the manufacturing sector can be determined. However, for the countries where the use of AI in the transportation sector is observed, it is successful in reversing the harmful effects of the transportation sector on the environment.

6.2 | Policy Recommendations

Based on the findings of this research, several policy suggestions may be made. In these recommendations, we prefer to focus on the moderating effects of AI. It is mostly shown in this context that incorporating AI into manufacturing does not considerably lessen environmental harm. In this direction, governments should mandate that AI-supported production facilities use clean energy sources (e.g., solar, wind, and hydro) instead of fossil fuels. Subsidies for AI-supported green production can encourage industries to adopt low-carbon technologies. Carbon pricing mechanisms should be introduced, where AI-supported factories that use fossil fuels face higher carbon taxes, while clean energy AI factories receive tax credits. In addition, policies should encourage AI applications in sustainable production and waste management (e.g., AI-supported recycling systems, predictive maintenance to reduce material waste). AI-based supply chain optimization should be encouraged to reduce carbon-intensive logistics and material waste. R&D incentives should be directed to environmentally friendly industrial processes such as AI-supported carbon capture in factories. Governments should promote AI in additive manufacturing (3D printing) to reduce material waste and emissions from traditional manufacturing methods.

On the other hand, based on the successful moderating role of AI on the environment in the transportation sector, governments should invest in AI-powered intelligent traffic management to reduce congestion and emissions in major cities such as Shanghai, Mumbai, Jakarta, Tokyo, and Bangkok. Dynamic AI-powered public transportation systems (adaptive bus routes, real-time planning) should be heavily subsidized to reduce reliance on private vehicles. AI-powered rail and subway network optimization should be expanded to provide seamless low-emission urban mobility. Tax incentives and subsidies for AI-powered EV production and use should be expanded, especially in China, India, and Indonesia, where fossil fuel-based transportation dominates. AI-powered predictive maintenance for fuel efficiency in logistics and freight transportation should be promoted. AI-powered autonomous public transportation can be piloted in Japan and Korea, where infrastructure supports automation. Green AI-powered logistics policies should be implemented to optimize supply chains and reduce empty truck trips. AI-powered route optimization for shipping and air transportation should be promoted to reduce fuel consumption and emissions. Port cities (Shanghai, Mumbai, Jakarta, Kuala Lumpur, and Bangkok) should implement AI-based emissions monitoring and pollution control measures.

Some policy suggestions for the countries may be made in light of the results. Carbon emissions are rising as a result of China's high energy intensity, fast IND, and rising UBN rate. One of the main causes of environmental deterioration is the industrial sector. Consequently, the industrial sector should encourage carbon capture technology and improve energy efficiency. To maximize resource use, industrial manufacturing processes should include AI technologies. Carbon emissions in India are rising as a result of unplanned UBN, fast population expansion, and energy reliance. This may be greatly aided by changes in the transportation industry. Therefore, in order to reduce wasteful fuel usage, AI-based traffic management systems have to be integrated into urban transportation networks. Furthermore, AI applications should focus on energy efficiency because the technology has little effect in the industrial sector. AI-assisted fleet management and logistics should be promoted in Indonesian transportation. To reduce pollution, industrial zones should implement energy efficiency regulations.

Given AI's beneficial effects on the environment, smart transportation systems should be further developed throughout the country of Japan. Investments in AI should go toward energy efficiency and emission control in the industrial sector as the environmental effect is less severe. To lower energy intensity, South Korea should install AI-based energy management systems in both residential and commercial spaces. The transportation industry should promote infrastructure investments for electric and AI-powered cars. Dense and sustainable UBN patterns need to be used in place of urban sprawl. Lastly, in order to decrease the usage of private vehicles, Thailand should create public transportation systems driven by AI. AI-powered solutions should be promoted in tandem with green industrial initiatives as the environmental effect of AI usage in industry is yet relatively small. AI-based consumption projections may help make urban energy planning more sustainable.

In addition, external geopolitical and economic circumstances may have a substantial influence on the study's conclusions. The implementation of AI-based carbon reduction technology is influenced by a number of variables, including regional geopolitical ties, international supply chain stability, and energy supply security. The deployment of these systems may be slowed or delayed, for instance, by trade limitations on the import of sophisticated sensor technology or AI software. Similar to this, the economic appeal of AI-powered optimization systems might sometimes change due to worldwide variations in energy costs. As a result, governments should create adaptable implementation strategies that include economic volatility and geopolitical risk scenarios, promote regional technological partnerships, and lessen reliance on outside sources by boosting local AI production capacity.

6.3 | Limitations and Future Directions

The study has some significant limitations. Firstly, the dataset used in the empirical analyses constitutes the most significant limitation. Indeed, with this observation period, the early development of AI technologies in the late 1990s and early 2000s, particularly in Southeast Asian countries, cannot be analyzed due to a lack of data. Similarly, recent international climate agreements and policy reforms such as COP27 and COP28 fall outside the scope of the study and cannot reflect new trends in countries' environmental strategies. Some methodological limitations can also be noted. For example, the study cannot observe the impact of regressors on the environment for different levels of environmental degradation. Utilizing quantile-based techniques in future studies could address this limitation.

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