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Nonlinear dynamics of environmental performance in Asia: The role of economic complexity, renewable energy, and green technologies

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ABSTRACT

The increasing environmental issues stemming from unsustainable practices highlight the necessity to assess and enhance global environmental performance. This research explored the factors influencing environmental performance (EPI) in 25 Asian countries from 2000 to 2022. Firstly, EPI was computed using indicators related to climate change, ecosystem vitality, and environmental health. Then, using a panel ARDL, the factors affecting the EPI were examined in two countries: total selected Asian countries and developing Asian countries. The components included the Economic Complexity Index (ECI), renewable energy consumption (REC), environmental technologies (ET), gross domestic product (GDP) per capita, and the Human Development Index (HDI). The findings revealed that Japan achieved the highest score on the EPI, whereas India and Pakistan received the lowest scores. Furthermore, Iran's score raises alarm due to significant challenges, especially in climate change and biodiversity. Additionally, the results rejected the Environmental Kuznets Curve (EKC) theory for all the Asian countries examined, demonstrating that the Environmental Complexity Index (ECI) is related to sustained enhancements in the Environmental Performance Index (EPI) and can support sustainability while decreasing environmental impact. However, a nonlinear relationship was discovered for developing Asian countries, supporting a variation of the EKC theory. While REC and ET are generally associated with positive short-term effects on EPI, particularly in developing countries, they can result in negative or intricate consequences in the long run. This emphasizes the critical need to adapt environmental policies to the varying developmental stages of countries, strengthen governance, and proficiently manage renewable technologies and energy through an integrated life cycle approach. Additionally, it encourages international partnerships to realize sustainable development in Asia.

1. Introduction

Unsustainable production and consumption patterns are among the primary drivers of three major environmental crises: biodiversity loss, climate change, and ecosystem degradation. These challenges arise from inefficient use of natural resources, significantly threatening environmental sustainability (Fatima et al., 2025; Menne et al., 2020; van Asselt and Green, 2023). Consequently, addressing environmental sustainability has become a key priority for the scientific community and policymakers (Romero and Gramkow, 2021) and is reflected in the Sustainable Development Goals (SDGs). Environmental protection has long been considered a practical approach in strategic decision-making for governments, policymakers, environmental organizations, and international institutions such as the United Nations (Sun and Razzaq, 2022; Umar et al., 2021a,b). The United Nations 2030 Agenda underscores the importance of environmental conservation, particularly in Goals 13 (climate action), 14 (life below water), and 15 (life on land) (UN, n.d.).

Sustainable development emphasizes meeting present needs without compromising the ability of future generations to satisfy their own requirements. This concept is essential for policymaking in countries aiming for sustainable economic growth (Akadiri et al., 2023; Drexhage and Murphy, 2010; Li et al., 2022; Rafique et al., 2022). A crucial component of sustainable development involves evaluating environmental performance, which requires reliable and comprehensive tools to measure environmental quality, identify inefficiencies, and assess economic and social impacts (Wang et al., 2023).

Research on environmental performance can be broadly categorized into two streams. The first stream employs composite indicators such as the Ecological Footprint (EF), carbon dioxide (CO_2) emissions, and

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Greenhouse Gas (GHG) measures (Appiah et al., 2023; Balsalobre-Lorente et al., 2024; Hassan et al., 2023; Li et al., 2023; Sadiq et al., 2022; Shokoohi et al., 2022; Tauseef Hassan et al., 2023; Wang et al., 2023), which provide insights into specific dimensions of environmental harm but overlook broader interactions with economic and technological factors. The second stream uses more comprehensive indices, notably the Environmental Performance Index (EPI), which evaluates multiple dimensions including air quality, water management, biodiversity, and climate change (Hsu and Zomer, 2016). While EPI provides a detailed assessment of environmental conditions, it has limited emphasis on economic factors and their interplay with the environment underscores the necessity for more comprehensive research in this domain.

Numerous studies have examined the effects of production and economic activities on environmental outcomes, often using economic growth and per capita income as proxies (Lv et al., 2024; Sheikhzeinoddin et al., 2022; Silva et al., 2024; J. Wang et al., 2024). While these indicators reflect general economic performance, they fail to capture structural changes, technological progress, and the complexity embedded in production systems (Arnaut and Dada, 2023; Balsalobre-Lorente et al., 2022; Chu, 2021; Hidalgo and Hausmann, 2009; Taskin et al., 2022). To address this limitation, Hidalgo and Hausmann (2009) introduced the concept of economic complexity, which reflects the knowledge, technical skills, and capabilities embedded in a country's production structure. The Economic Complexity Index (ECI) quantifies this embedded knowledge and technology, providing insights into a country's economic sophistication and its potential influence on environmental performance (Khan et al., 2022; Neagu and Teodoru, 2019).

Economic complexity, by integrating modern technologies, research and development, and eco-friendly products and services, can enhance energy efficiency, reduce reliance on outdated or polluting technologies, and promote sustainable development (Balsalobre-Lorente et al., 2024; Huang et al., 2022). However, rapid technological advancements, while central to economic growth, may also increase energy consumption, particularly from fossil fuels, potentially exacerbating environmental degradation. This tension highlights the need to incorporate ECI into models assessing nonlinear and interactive effects of economic, technological, and environmental factors, complementing indicators like the EPI (Numan et al., 2023; Umar et al., 2021a,b).

The growth of global production and economic activities has simultaneously increased energy demand (Sadiq et al., 2022; Yilanci and Pata, 2020). This demand, primarily met through fossil fuels, poses two main challenges: pollutant emissions that degrade environmental quality and economic instability due to fluctuating fuel prices. These challenges have led governments and companies to promote renewable energy adoption (Poinssot et al., 2016). Renewable energy is vital for sustainable development, supporting decarbonization, net-zero carbon targets, and international goals such as the UN 2030 Agenda and the Paris Agreement (Bai et al., 2020; Baloch et al., 2020; McGee and Greiner, 2019; J. Wang, 2024). According to the International Energy Agency (IEA), renewable energy's share of total consumption rose from 10.5 % in 2017 to 13 % in 2023 and is projected to reach 20 % by 2030. Despite this trend, studies show inconsistent assessments of the environmental impacts of renewable energy (Wang, 2024). Integrating renewable energy into models alongside economic complexity and environmental performance indicators allows a more comprehensive understanding of its role in promoting sustainability.

Green technologies also play a crucial role in environmental conservation. Technological advancements, particularly in the energy sector, can enhance resource efficiency and reduce the environmental impacts of economic activities (Wang et al., 2021; Yan et al., 2022). Green innovations contribute not only to environmental protection but also to social and economic development (Klewitz and Hansen, 2014; Omri, 2020). However, their effectiveness in addressing climate change, environmental health, and biodiversity varies (Majerník et al., 2023; Nawaz et al., 2023). Previous studies often examine renewable energy, technological innovation, and economic complexity separately, overlooking their interdependent and nonlinear effects, especially in Asian countries. A summary of previous studies based on their focus, applied methods, and key findings is presented in Table 1.

This study addresses these gaps by integrating economic complexity, renewable energy, and green technologies into a unified analytical

Table 1
Summary of previous studies: Focus, methods, and key findings.

Study	Focus	Methods	Key Findings
Abbas et al. (2024)	Green patents, R&D, and energy use in low-carbon cities in China	CS-ARDL, Q-ARDL, Granger's non-causality	Green patents and R&D spending significantly reduce carbon emissions. Validates EKC theory in the context of China's low-carbon cities.
Saqib et al. (2024)	Environmental innovations and financial development in high ecological footprint countries	Panel causality approach	Environmental innovations, financial growth, and renewable energy positively influence ecological sustainability, while non-renewable energy is harmful.
Saqib et al. (2024)	ICT, renewable energy, and human capital in top polluting economies	CS-ARDL, econometric techniques	Eco-friendly ICT and renewable energy reduce carbon footprints; financial development and economic growth influence carbon emissions.
Feng et al. (2014)	Green technologies, renewable energy, and economic complexity in BRICS countries	CS-ARDL, panel data models	Green technologies and renewable energy significantly reduce ecological footprint, while economic complexity can harm the environment.
Hassan et al. (2023)	Economic complexity, nuclear energy, globalization, and ecological footprint	CS-ARDL, CCEMG, AMG estimation methods	Economic complexity increases ecological footprints; nuclear energy helps reduce ecological pressures in OECD countries
Wang et al. (2023)	The impact of energy structure and industrial shifts on ecological footprint	Panel threshold regression models	Renewable energy consumption reduces ecological footprint; higher industrial complexity increases environmental pressures unless mitigated by renewable energy.
Khan et al. (2022)	Economic complexity, technology advancements, and ecological footprint in the USA	DARDL, KRLS models	Economic complexity increases environmental pressures, but nuclear energy and technological improvements reduce the footprint.
Li et al. (2023)	Renewable energy and its impact on reducing ecological and carbon footprints	Panel threshold regression model	Renewable energy consumption significantly reduces carbon and ecological footprints, especially in low-income countries
Wang et al. (2023)	Economic complexity, energy structure, and labor force on environmental impacts	Threshold regression and static models	Increased economic complexity leads to a higher ecological footprint, but renewable energy consumption helps mitigate these effects

framework to assess their combined influence on the Environmental Performance Index (EPI). By doing so, it evaluates how these factors improve environmental quality without compromising economic growth, providing nuanced insights for policymakers and stakeholders. Asian countries, characterized by heterogeneous development levels, energy structures, and environmental conditions, are the focus, allowing exploration of differential impacts across developed and developing contexts. The conceptual linkages among the key variables are illustrated in Fig. 1. The diagram illustrates the interrelationships between the main variables and the Environmental Performance Index (EPI). Economic complexity (ECI), renewable energy consumption (REC), and environmental technologies (ET) may exert both positive and negative effects on environmental performance. Human development (HDI) generally improves EPI, while higher GDP levels often increase environmental pressures, resulting in negative impacts. Anti-globalization, by altering trade openness, investment flows, and technology diffusion, is theorized to influence EPI positively, though the pathways remain complex.

In summary, prior research has primarily focused on isolated factors or single indicators of environmental performance, often neglecting nonlinear, interactive, and context-specific effects. This study fills the gap by examining the simultaneous effects of economic complexity, renewable energy, and green technologies on environmental performance, offering novel insights and policy-relevant guidance for countries at various stages of development.

In this regard, the EPI and its calculation processes were initially described. Afterward, the methodology utilized to analyze the interaction effects of economic complexity, renewable energies, and clean technologies on this index was clarified. Finally, the results from the modeling and statistical analysis were presented, and the findings were discussed with an emphasis on the differences observed between all selected Asian countries and developing Asian countries.

2. Materials and methods

2.1. Environmental Performance Index

The calculation of the EPI is delineated into six distinct processes. The initial step involves the formulation of the theoretical framework. This study utilized the EPI from the 2024 report to assess the environmental status of the study area (EPI, n.d.). In the subsequent step, to finalize the data set, missing values in the variables (considering they constituted less than 15 % of the total observations) were substituted utilizing statistical interpolation techniques (Schuschny and Soto, 2009). Subsequently, to guarantee the validity of the results, factors lacking substantial connection with other variables in the model were excluded by multivariate analysis (OECD, 2008). This study utilized data from the Yale University website, encompassing 25 variables across three dimensions: climate change, ecosystem vitality, and environmental health, relevant to the specified period. Table 2 illustrates the specifics of the data.

The next step is data normalization. Since the variables are represented by different units or scales, it is vital to apply a dimensionless process to each indicator to eliminate the effects of varying dimensions on the evaluation results. In order to normalize the data, Box-Cox and Johnson transformation methods are used. The Johnson transformation method was selected as the preferred approach in this research due to its ability to manage negative and zero data (Sheikhzeinoddin et al., 2022).

After data normalization, it is essential to ascertain the suitable weight for each variable. The allocation of weights in multi-criteria situations is a vital aspect of the decision-making process. Multiple approaches exist for determining weight, including principal components, Data Envelopment Analysis (DEA), expert involvement methods, entropy techniques, Inter-Criterion Correlation (CRITIC), and variance-based methodologies. (Libório et al., 2024; Pliego-Martínez et al., 2024; Pourhabib Yekta et al., 2018). In this study, the CRITIC method was used to determine the weights of the indicators. Given the operational limitations associated with subjective weighting techniques, such as surveys or expert opinions, in macro and cross-country studies, the CRITIC method is appropriate for this analysis. This method determines weights exclusively based solely on the statistical characteristics of the data, particularly the dispersion (standard deviation) of each variable and its correlation (covariance) with other variables, thus eliminating the need for subjective evaluation, which is impractical at the national level (Zhong et al., 2023). Eq. (1) was used for this purpose:

$$c_j = \delta_j \times \sum_{k=1}^{m} \left(1 - r_{jk}\right) \tag{1}$$

In Eq. (1), c_j denotes the weight coefficient, δ_j signifies the standard deviation, m indicates the number of criteria, j represents the specific criterion, and r_{jk} refers to the correlation coefficient between variables. Subsequently, in Eq. (2), the derived weight coefficient c_j is divided by the total of the weight coefficients $\sum_k^m c_j$ to ascertain the weight of the variables (w_j).

$$w_j = \frac{c_j}{\sum_k^m c_j} \tag{2}$$

Subsequent to determining the weight of each sub-index, Eq. (3) was ultimately employed to compute the composite EPI (OECD ILibrary, n.d):

$$\mathrm{EPI} = ((Eco \times w_{eco}) + (Env \times w_{env}) + (Cc \times w_{cc})) \tag{3}$$

In this regard, Cc,[1] Eco,[2] Env[3] are related to the sub-indices of climate change, ecosystem vitality and environmental health, respectively, and w reflects the weight of each of these sub-indices.

In this study, the EPI was calculated for the selected countries of the Asian continent in the period 2000–2022. This indicator is defined between 0 and 1, so higher values indicate better environmental performance compared to other countries. Therefore, countries that have received a higher EPI score indicate more positive environmental performance compared to other Asian countries. It should be noted that the required data were collected for two groups of Asian countries: five high-income countries—Singapore, South Korea, Cyprus, the United Arab Emirates, and Japan—and twenty developing or transition countries, namely Armenia, Azerbaijan, Bangladesh, Georgia, India, Indonesia, Iran, Jordan, Kazakhstan, Lebanon, Malaysia, Pakistan, the Philippines, Russia, Sri Lanka, Thailand, Turkey, China, Uzbekistan, and Vietnam. This selection was made based on the availability of data from these countries, given their economic and environmental importance.

2.2. Identifying determinants influencing the EPI

The purpose of this section is to identify the elements influencing the EPI by selecting the variables of economic complexity (ECI), renewable energy consumption (REC), gross domestic product per capita (GDP), environmentally related technology (ET), and human development index (HDI) in selected countries. Information related to these variables is illustrated in Table 3.

This study designated the EPI as the dependent variable. At the same time, the ECI, HDI, ET, GDP, and REC were identified as independent variables. The EKC hypothesis test was also analyzed. This hypothesis posits that the link between the EPI and ECI may exhibit an inverted U-shape. The ECI variable, its square (ECI^2), and its cube (ECI^3) were utilized to analyze this link. The econometric model employed to examine the EKC hypothesis is as Eq. (4):

[1] - Climate Change.
[2] -Ecosystem Vitality.
[3] - Environmental Health.

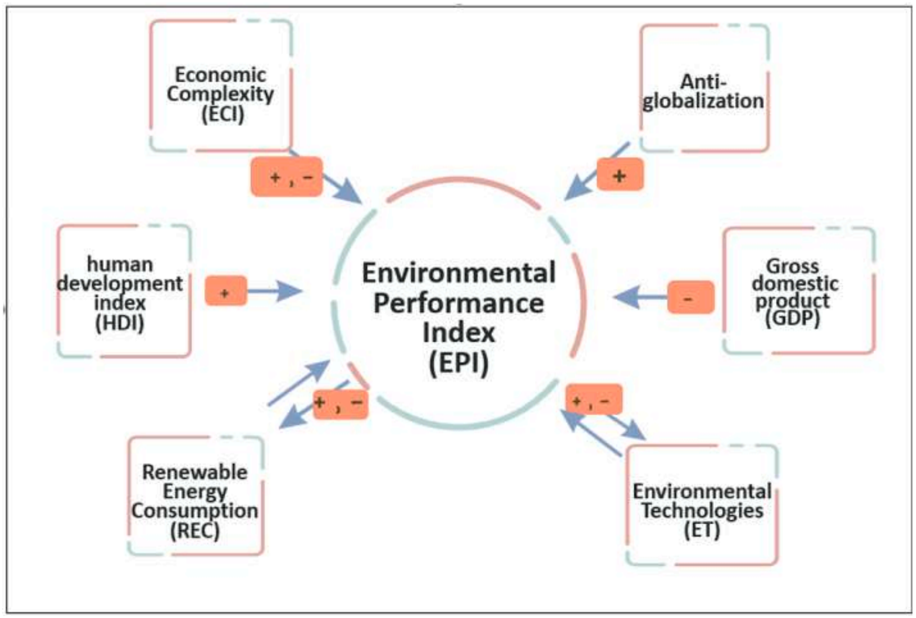

Fig. 1. Interrelationships between variables influencing the Environmental Performance Index (EPI).

$$LN\,EPI = \alpha_0 + \alpha_1 \ln ECI_{it} + \alpha_2 Ln\,ECI^2{}_{it} + \alpha_3 Ln\,ECI^3{}_{it} + \alpha_4 Ln\,ET_{it} + \alpha_5 Ln\,GDP_{it} + \alpha_6 Ln\,REC_{it} + \alpha_7 Ln\,REC_{it} + \varepsilon_{it} \quad (4)$$

In this research, the natural logarithm transformation[4] is applied to all variables to mitigate the issue of multicollinearity within the model and enhance the evaluation's precision. In this framework, 'i'' denotes the cross-sections (25 countries in Asia regian), and 't' is time. If the EKC is validated, the coefficient of the ECI variable in Eq. (4) ought to be positive, while the coefficient of ECI[2] should be negative and statistically significant (Alvarado and Toledo, 2017; Sheikhzeinoddin et al., 2022; Tarazkar et al., 2021). It is important to highlight that the model was estimated once for all selected Asian countries and once for selected developing Asian countries. In addition, since REC exert diminished adverse environmental effects relative to fossil fuels, it is anticipated to enhance the EPI (Ahmad et al., 2020, 2021; Balsalobre-Lorente et al., 2024). Furthermore, as the HDI) underpins equitable opportunities, it is expected to enhance both sustainable development and EPI (Mohammadi and Zarif, 2018). It is crucial to acknowledge that economic growth, which is a key factor in development, frequently associates with environmental deterioration. Consequently, because of this contradiction, it is anticipated that the correlation between GDP and EPI will exhibit a negative and statistically significant relationship in the analyses (Sethi et al., 2020; Alvarado and Toledo, 2017). Developing and applying environmentally focused technology can significantly improve EPI and promote sustainable development (Shahid et al., 2024).

This study used advanced econometric approaches to survey the relationship between different variables and test the Kuznets environmental hypothesis. First, to ensure the suitability of the data for analysis, cross-sectional dependence tests were conducted using the methods proposed by Pesaran, Friedman, and Freeze (Pesaran, 2004). The tests assessed the existence or nonexistence of dependence among cross-sectional units in the data. Subsequently, second-generation panel stationarity tests were performed to assess the extent of variable accumulation and confirm the absence of spurious regression (CIPS and CADF tests) (Im et al., 2003; Breitung and Pesaran, 2008). Because these tests can compensate for heterogeneity and cross-sectional dependence, they were more appropriate than first-generation tests. This method facilitates the estimation of three distinct estimators: MG, PMG, and DFE (Pesaran et al., 1999). The PMG estimator, serving as an intermediary between MG and DFE, permits variations in short-run coefficients among groups while presuming uniformity in long-run coefficients.

3. Results

3.1. Results of the calculated EPI

The results from the computation of the weight assigned to each dimension (refer to Appendix Tables 1 and 2) reveal that the ecosystem vitality dimension holds the highest weight (0.375), followed by environmental health (0.343) and climate change (0.28). The findings of the calculated EPI showed that Japan, as a prominent Asian country, has the highest EPI due to comprehensive environmental policies, investments in renewable energy, technological innovation, and participatory governance (Sarkar et al., 2024; env.go.jp, n.d.; Ministry of Foreign Affairs of Japan, n.d.). In contrast, India has the lowest EPI, encountering issues such as severe air pollution, limited freshwater resources, and inadequate biodiversity conservation, which are due to financial constraints, ineffective policies, and unsustainable exploitation of natural resources (Brauer et al., 2024; SIWI, n.d.; Farhadinia et al., 2022). In addition, Pakistan exhibited subpar performance in the EPI, attributed to its dependence on coal and the detrimental effects of climate change, exemplified by the 2022 floods; thus, the advancement of renewable energy has been suggested as a pivotal strategy to enhance the nation's environmental conditions (IEA; Klein et al., 2023; Block et al., 2024). Fig. 2 shows the average of the calculated EPI for the selected Asian countries.

[4] This study employed the Signed Log Transformation approach to address negative and zero values in the data. This technique includes a constant value to all data before applying the natural logarithm. This approach is employed in economic research to mitigate issues arising from zero and negative values (West, 2022).

Table 2
The 2024 EPI framework.

Policy Objective	Issue Category	Indicator	Abbreviation	Unit Of Measurement
Climate Change	Mitigation	Projected emissions in 2050	GHN	Gg
		GHG trend adjusted by emissions per capita	GTP	unitless
		GHG trend adjusted by emissions Intensity	GTI	unitless
		Adjusted emissions growth rate for black carbon	BCA	Gg
		Adjusted emissions growth rate for nitrous oxide	NDA	Gg
		Adjusted emissions growth rate for F-gases	FGA	Gg CO2-eq
		Adjusted emissions growth rate for methane	CHA	Gg
		Adjusted emissions growth rate for carbon dioxide	CDA	Gg
Env. Health	Sanitation & Drinking Water	Unsafe drinking water	UWD	Age-standardized DALYs/100k people
		Unsafe sanitation	USD	Age-standardized DALYs/100k people
	Air Quality	Anthropogenic PM2.5 exposure	HPE	Micrograms per cubic meter of air (μg/m3)
		Household solid fuels	HFD	Age-standardized DALYs/100k people
		Ozone exposure	OZD	Age-standardized DALYs/100k people
		NOx exposure	NOD	Age-standardized DALYs/100k people
		SO2 exposure	SOE	Concentration (ppm)
		CO exposure	COE	Concentration (ppm)
		VOC exposure	VOE	Concentration (ppm)
	Heavy Metal	Lead exposure	LED	Age-standardized DALYs/100k people
Ecosystem Vitality	Agriculture	Sustainable Nitrogen Management Index	SNM	kg/ha
	Biodiversity & Habitat	Species Protection Index	SPI	%
		Red List Index	RLI	%
	Air Pollution	Adjusted emissions growth rate for sulfur dioxide	SDA	Gg
		Ozone exposure KBAs	OEB	PPM
		Ozone exposure croplands	OEC	PPM
		Adjusted emissions growth rate for nitrous oxides	NXA	unitless

Reference:https://epi.yale.edu/.

Table 3
Variables Definition and data sources.

Variable name	Signs	Unit of measurement	Data source
Environmental performance	EPI	Environmental performance index	calculated in this study
Economic Complexity	EC	Economic Complexity Index	The Atlas of Economic Complexity
Renewable Energy consumption	REC	Percentage of total final energy consumption	International Energy Agency
Income per capita (PPP)	GDP Per Capita	constant 2021 international $	World Bank
Environmental Technologies	ET	Number of patents, with country fractional value	OECD. Stat
Human Development Index	HDI	Human Development Index	United Nations (IEA)

Iran's Environmental Performance Index (EPI) falls below the regional average when compared to other Asian countries under examination. This underperformance can be attributed to two primary factors. First, the adverse impacts of climate change and biodiversity loss—driven by methane emissions, inefficient waste management practices, and elevated greenhouse gas concentrations—have significantly compromised Iran's environmental indicators (OECD & FAO, 2023; IPCC et al., 2023). Second, the country exhibits inadequate outcomes in areas such as species conservation, ozone layer protection within ecologically sensitive regions, and nitrogen regulation in agriculture. These deficiencies are closely associated with habitat degradation and overhunting (IUCN, 2023), industrial and vehicular pollution (NASA, 2023; UNEP, 2023), as well as the excessive use of nitrogen-based fertilizers (OECD & FAO, 2023). The fundamental issue contributing to these challenges is the absence of a well-defined and enforced environmental policy in this country.

3.2. Results of impacts of different variable on EPI

This section employed panel data and the Panel ARDL model to examine the impacts of different variables on the EPI in selected Asian countries and test the Kuznets environmental hypothesis. This methodology was chosen for its effectiveness in handling panel data with varying stationarities and for modeling both long-term and short-term relationships within a cohesive framework. In contrast to methods like PSTR that focus on threshold effects, ARDL facilitates a comprehensive analysis of variable impacts over time (Pesaran, 2004). Moreover, spatial econometrics, which emphasizes spatial dependencies, is unsuitable for time-series and cross-sectional panel data (Anselin, 1988). Compared to Panel Quantile regression, which emphasizes

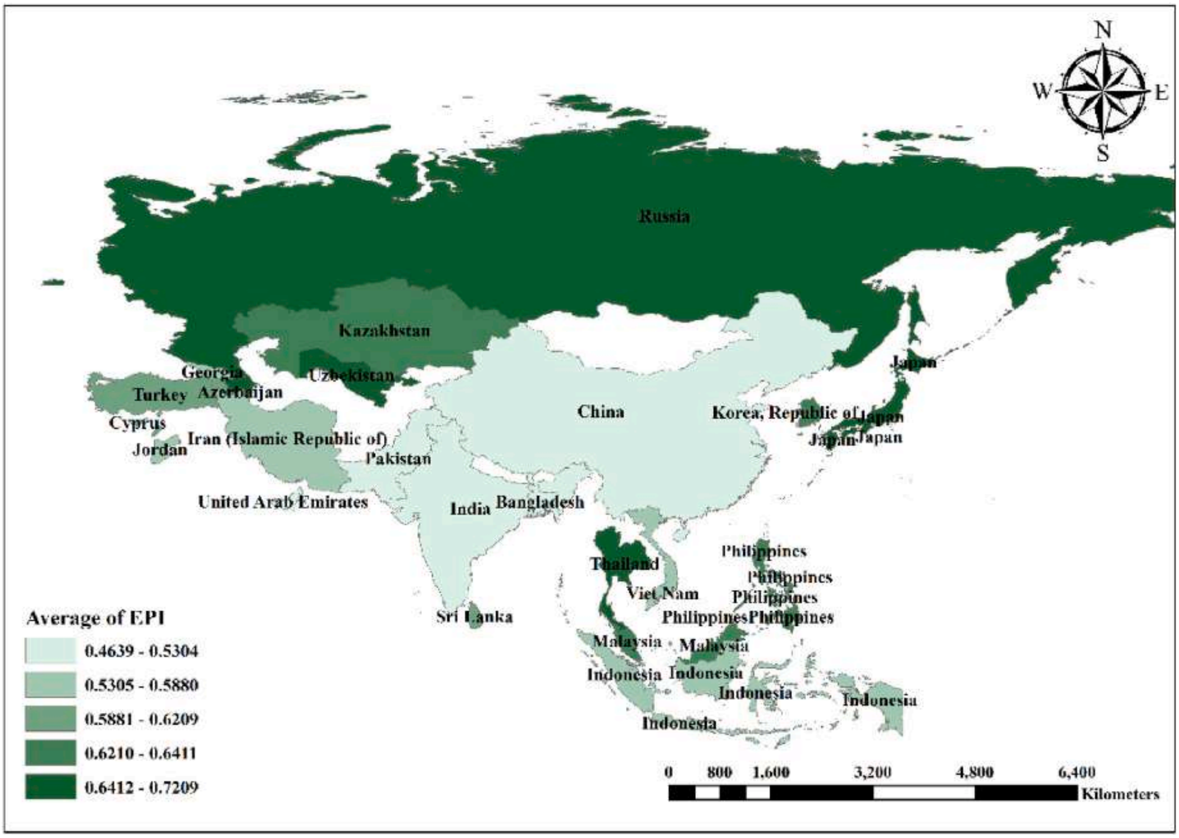

Fig. 2. Average of the calculated EPI (2000–2022).

Table 4
Cross-sectional dependence tests.

Variables	Statistic	p-value
LnEPI	20.146***	0.00
LnECI	0.683	0.49
$LnECI^2$	1.02	0.30
$LnECI^3$	1.41	0.15
LnREC	−1.21	0.22
LnET	33.53***	0.00
LnGDP	77.762***	0.00
LnHDI	57.209***	0.00

Reference: Research findings.

Table 5
Results of the panel unit root test for all variables expressed in natural logarithms.

Unit root test					
Variables at level	Pesaran CIPS		CADF		Result
LnEPI	−1.18	0.10≤	−1.595	0.95	Non-stationary
LnECI	−2.51	0.10≤	−1.458	0.93	Non-stationary
$LnECI^2$	2.32-***	0.01≥	2.597-*	0.06	I (0)
$LnECI^3$	2.42-*	0.10≥	−1.702	0.9	I (0) or Nonstationary
LnREC	−1.651	0.10≤	−1.33	0.97	Non-stationary
LnET	3.074-***	0.01≥	−2.264	0.59	I (0) or Nonstationary
LnGDP	2.459-***	0.01≥	−1.749	0.50	I (0) or Nonstationary
LnHDI	3.115-***	0.01≥	2.22-***	0.008	I (0)
Variables at first difference					
Δ(LnEPI)	2.908-***	0.01≥	2.66-**	0.03	I (1)
Δ(LnECI)	4.822-***	0.01≥	2.79-***	0.007	I (1)
$\Delta(LnECI^2)$	5.096-***	0.01≥	3.309-***	0.00	I (1)
$\Delta(LnECI^3)$	4.889-***	0.01≥	2.258-***	0.005	I (1)
Δ(LnREC)	4.436-***	0.01≥	2.65-**	0.03	I (1)
Δ(LnET)	5.543-***	0.01≥	2.84-***	0.00	I (1)
Δ(LnGDP)	4.766-***	0.01≥	2.130-**	0.02	I (1)
Δ(LnHDI)	4.668-***	0.01≥	2.46-***	0.00	I (1)

Reference: Research findings.

quantile-specific effects, ARDL provides more dependable outcomes in analyzing dynamic relationships and is better suited for time-series panel data that includes both stationary and non-stationary variables (Balsalobre-Lorente et al., 2022; Huo et al., 2024).

Considering the potential for cross-sectional reliance among the countries analyzed, Pesaran's CD test (Pesaran, 2004) was employed to confirm that this dependence did not influence the modeling outcomes. Table 4 presents the test findings, demonstrating the presence of cross-sectional dependence in most data.

This study, in contrast to previous research employing first-generation tests for stationarity, examined the stationarity test under cross-sectional dependency, as recommended by Pesran, based on the results of the cross-sectional dependence test. Two Pesran CIPS tests and CADF test were employed (Im et al., 2003).Table 5 presents the outcomes of the panel unit root tests employing the CIPS and CADF methodologies for seven logarithmic variables (EPI, ECI, ECI,[2] ECI,[3] REC, ET, GDP, HDI) analyzed for both level and first-difference data.

Accordingly, most variables are cointegrated at the level, while others are at the first difference. The results of the stationarity test validate the appropriateness of employing the panel-wide lags (ARDL)

Table 6
Results from PMG, MG and DFE Panel ARDL estimators in all selected Asian countries.

	PMG		MG		DFE	
	Long run	Short-run	Long run	Short-run	Long run	Short-run
LnECI	0.010***		1.43		0.006	
	0.001		0.11		0.92	
$LnECI^2$	0.019***		−0.83		0.004	
	0.00		0.13		0.105	
LnREC	0.053-***		−0.01		−0.009	
	0.00		0.92		0.67	
LnET	0.036-***		0.11-**		−0.01	
	0.00		0.03		0.38	
LnGDP	0.51-*		0.76-**		0.12-**	
	0.09		0.03		0.04	
LnHDI	1.71***		3.54**		0.13	
	0.00		0.04		0.65	
Error Correction		0.10-***		0.26-***		0.11-***
		0.00		0.00		0.00
Δ(LnECI)		−0.032		−0.21		−0.0006
		0.52**		0.14		0.28
$\Delta(LnECI^2)$		0.039		0.12		0.00001
		0.36		0.14		0.93
Δ(LnREC)		0.046**		0.003		0.01***
		0.07		0.84		0.008
Δ(LnET)		0.006***		0.015**		0.001
		0.02		0.01		0.18
Δ(LnGDP)		−0.03		0.02		0.03-*
		0.49		0.61		0.08
Δ(LnHDI)		−0.01		−0.42		0.0005
		0.94		0.12		0.99
Constant		0.56***		0.45		0.09
		0.00		0.44		0.22
Observations	550	550	550	550	550	550

Reference: Research findings.

methodology within the panel data framework. The model was estimated using the mean group (MG), pooled mean group (PMG), and dynamic fixed effects (DFE) estimators within the framework of the PANEL ARDL methodology. Table 5 summarizes the results from these three estimators for all selected Asian countries, while Table 6 illustrates the results for developing Asian countries. The Hausman test was subsequently employed to identify the efficient estimator. The Hausman test results indicate that the null hypothesis of homogeneity of long-run coefficients across sections, together with the superiority of the PMG estimator over the MG and DFE estimators, is not rejected. Consequently, in this study, the results of the PMG estimator are explained.

Table 5 presents the results of the PMG estimator, which showed that all variables' coefficients are significant at the 99 % and 90 % significance levels in the long run for all selected Asian countries by theoretical expectations. The coefficients associated with the ECI and its square are positive and statistically significant. However, the coefficient of the ECI^3 was not significant; hence, this variable was removed from the model. Therefore, these results reject the EKC hypothesis for selected Asian countries. This study's findings demonstrate that increasing the ECI consistently correlates with enhanced environmental quality, and the inverted U-shaped relationship posited by the EKC hypothesis is not evident in this context.[5] The results suggest that ECI can serve as a beneficial and sustainable element in enhancing environmental quality, bypassing the preliminary phases of environmental degradation posited by the EKC hypothesis. The results of this study contest the EKC hypothesis and indicate that economic complexity may offer a distinct and more efficacious route to attaining ecologically sustainable growth. In summary, heightened ECI enhances the EPI in the study area over the long-run, with this enhancement occurring at an accelerating rate. Consequently, as the economies of these countries grow more intricate, the EPI rises, and environmental pressure diminishes. This result may stem from the advancement of clean technologies, heightened environmental consciousness, enhanced resource efficiency, and robust environmental policies. These findings are consistent with (Tabash et al., 2024; Tchapchet Tchouto, 2023) research.

The estimation results also indicated that the application of renewable energies has varied effects on the EPI in the short and long run. In the long run, the consumption of renewable energies has a negative effect on EPI, with a significant coefficient of −0.05. This means that a one percent increase in renewable energy consumption leads to a 0.05 percent decrease in EPI and an increase in its destruction in the long run. This conclusion is consistent with several prior reports (Cherni and Essaber Jouini, 2017; Mehdi and Slim, 2017). However, the results demonstrate that renewable energies can improve the environment in the short run. A one percent increase in the consumption of these energies significantly increases EPI by 0.04 percent. This beneficial effect is likely because renewable energies replace fossil fuels in short run (such as oil and gas) and, as a result, produce less pollution and cause less damage to the environment. This conclusion is consistent with numerous prior reports, including (Kostakis, 2024).

In addition, the results indicated that the impact of environmental

[5] The EKC hypothesis posits an inverted U-shaped correlation between economic development and environmental quality. This indicates that environmental degradation escalates during the initial phases of economic growth, but subsequently, as income surpasses a specific threshold, environmental quality is enhanced with continued development (Grossman and Krueger, 1995).

Table 7
Results from PMG, MG and DFE Panel ARDL estimators in developing countries.

	PMG		MG		DFE	
	Long run	Short-run	Long run	Short-run	Long run	Short-run
LnECI	0.003**		−0.98		0.009	
	0.04		0.41		0.9	
$LnECI^2$	0.009***		−1.71		0.003	
	0.00		0.23		0.23***	
$LnECI^3$	0.001-***		−0.57		0.00	
	0.00		0.5		0.9**	
LnREC	0.27***		1.27**		0.02	
	0.00		0.04		0.54	
LnET	0.07-***		−0.2		−0.003	
	0.00		0.39		0.79	
LnGDP	0.35-***		−2.79		−0.04	
	0.00***		0.3		0.56	
LnHDI	1.9		12.6		−0.28	
	0.00***		0.3		0.45	
Error Correction	0.12-**		0.32-***		0.1-***	
	0.01		0.00		0.00	
Δ(LnECI)		0.003		−0.02		−0.001
		0.76		0.36		0.3
$\Delta(LnECI^2)$		0.007		0.04		−9.9e
		0.76		0.38**		0.9
Δ(LnECI3)		0.04		0.03		0.0003
		0.12		0.68		0.57
Δ(LnREC)		0.03		−0.009		0.013**
		0.36		0.69		0.03
Δ(LnET)		0.007**		0.008*		0.001
		0.02		0.09		0.3
Δ(LnGDP)		0.002		0.08*		0.04-**
		0.9		0.09		0.06
Δ(LnHDI)		−0.48		−0.25		−0.02
		0.76		0.15		0.7
Constant		0.39**		0.79*		−0.02
		0.01		0.09		0.7
Observations	440	440	440	440	440	440

Reference: Research findings.

technology on EPI is contingent upon the time frame. A positive and significant correlation was identified between these two variables in the short run, aligning with prior research and indicating that the initial implementation of these technologies can result in environmental enhancement (Javed et al., 2024; Omri, 2020; X. Wang et al., 2022). In the long run, a negative and significant correlation was identified, indicating that each 1 % increase in the utilization of these technologies resulted in a 0.03 % decline in the EPI. The long run decline in EPI can be ascribed to various factors. Many environmental technologies are poorly implemented or do not meet the criteria, leading to negative consequences and worsening environmental deterioration. Secondly, utilizing these technologies may lead to increased production and consumption, imposing additional pressure on natural resources and compromising the initial advantageous effects of the technology. Thirdly, excessive technological advancements often neglect social and economic dimensions; sustainable development requires a comprehensive and equitable assessment of environmental, social, and economic factors. The high costs associated with various environmental technologies and their limited accessibility, especially in developing countries, impede their widespread and practical application, thereby obstructing the achievement of expected long-term advantages (Huo et al., 2024). Moreover, the negative coefficient for infrastructure in the fixed effects model highlights that infrastructure alone does not necessarily improve environmental outcomes. Regional disparities, inequitable access, and poor management can lead to unintended adverse effects. Sensitivity analyses using alternative infrastructure indicators and regional sub-samples confirm that unevenly distributed infrastructure may exacerbate environmental harm. This finding aligns with the broader literature, suggesting that technological or infrastructural interventions may fail to achieve their intended environmental benefits if systemic and contextual factors are not addressed (Climate Sustainability Directory, n.d.).

In addition to technological factors, the research revealed that macroeconomic and social variables significantly affect EPI. The results indicated that a 1 % increase in GDP is associated with a 0.51 % reduction in EPI. The ongoing extraction of natural resources, fossil fuels, and the activities of polluting industries remain the primary catalysts for economic growth in numerous Asian countries. This growth paradigm results in heightened greenhouse gas emissions, ecosystem deterioration, and contamination of water and soil resources. Insufficient environmental policies, lax regulatory enforcement, and a lack of investment in sustainable technologies have led to economic growth that negatively impacts environmental quality. Improving the Human Development Index (HDI) leads to a 1.71 percent increase in the

Environmental Performance Index (EPI). This highlights the importance of enhancing social and human conditions to achieve environmental sustainability. The results are consistent with the findings of the study conducted by Balsalobre-Lorente et al. (2024).

The error correction component's coefficient, reflecting the short-term adjustment rate, was determined to be significant and measured at −0.10. Consequently, in an unforeseen shock, 0.10 percent of the departure from the long-term equilibrium is rectified in each period.

Subsequently, to analyze the specific impact of renewable energies and ecologically related technologies on the developing countries of Asia, the model has been evaluated independently for these countries, with the findings detailed in Table 7. This analysis examines the model's outcomes, emphasizing variables that exhibit unique behavior within this group of countries in light of specific findings aligning with the broader model.

Based on the results of the PMG model estimates for developing Asian countries, presented in Tables 5 and it is shown that the coefficients of all variables, in the long run, are statistically significant at the 99 % and 90 % significance levels, according to theoretical expectations. In this regard, the findings of the research indicated that the first and second powers of the economic complexity index positively influence the EPI, whereas its third power negatively impacts the EPI. Therefore, there is a nonlinear (inverted U-shaped) relationship between ECI and EPI. This means that in the preliminary and intermediate stages of growing economic complexity, countries progress towards manufacturing more advanced, technology-intensive, and higher value-added products. This development is often accompanied by advancements in energy efficiency, environmentally sustainable technological innovations, and a more judicious use of resources. As a result, EPI improves. However, at high levels of economic complexity (cubic), the reverse trend may begin. Countries turn to highly complex and resource-intensive industrial production, which may be accompanied by increased energy consumption, industrial waste, and pressure on ecosystems. This can decrease the EPI, especially if environmental policies are not strengthened in parallel with industrial development. These results are consistent with study (Balsalobre-Lorente et al., 2024).

In this regard, the results showed that rapid economic development (GDP) in these countries is often accompanied by environmental degradation. This finding is consistent with the research conducted by Andrew et al. (2024). In addition, enhancing the HDI results in a 1.71 % increase in EPI. This underscores the significance of improving social and human conditions for environmental sustainability in these countries. The outcome aligns with the study's findings by Balsalobre-Lorente et al. (2024).

Furthermore, the results showed that, over the long term, renewable energy consumption positively and significantly influences the environmental performance of developing Asian countries; specifically, a one percent increase in renewable energy consumption correlates with an average improvement of 0.27 percent in the EPI. This finding, aligned with prior research by (Kostakis, 2024; Özkan et al., 2025; Wang et al., 2024; Wang, 2024), substantiates the significance of renewable energy advancement as a crucial element in attaining sustainable development and enhancing environmental quality. Therefore, it is imperative to implement supporting regulations, attract investment, and establish suitable infrastructure in the renewable energy sector. The disparity in outcomes between Asian developing countries and the other countries examined can be ascribed to the nascent phases of economic development and the evolving energy frameworks in these countries. These circumstances have facilitated the swift substitution of polluting energy sources with renewable energies, thereby positively influencing the environment.

4. Conclusion

This study presents a comprehensive examination of the elements affecting environmental performance in selected Asian countries. The computed Environmental Performance Index (EPI) results reveal that Japan have excelled in environmental efforts, largely due to strong legislation and effective governance. Conversely, India, Pakistan and Iran are grappling with significant issues, including air pollution, water shortages, and climate change, underscoring the necessity for effective governance and thorough environmental policies.

Unlike many studies that confirm the EKC hypothesis, the findings of this research indicate the absence of an inverted U-shape in the in selected Asian countries, suggesting that economic complexity may instead foster better environmental outcomes when supported by institutional efficiency, clean technology adoption, and policy frameworks. In contrast, a nonlinear, inverted U-shaped relation between ECI and EPI was found in developing countries within Asia. Various factors contribute to the differences in these trends, including levels of technological advancement, institutional efficiency, and the quality of environmental governance. This denotes that countries in the early stages of economic progress may face amplified environmental challenges as their economic complexity increases.

The study also makes an important contribution by distinguishing between short-term and long-term impacts of renewable energy and environmental technologies. This nuanced understanding is crucial for global policymaking, as it illustrates that energy transitions and technology adoption require long-term commitment and robust implementation strategies to ensure lasting benefits.

Furthermore, highlighting the negative role of GDP and the positive effect of HDI on environmental performance reinforces the global argument that human development—through education, health, and awareness—plays a more sustainable role than income growth alone in improving environmental outcomes.

Considering these findings, several strategic recommendations are suggested to enhance environmental performance in Asian countries:

1 Strengthen Environmental Governance: Drawing on Japan's success, countries such as India, Pakistan, and Iran should prioritize the development of robust regulatory systems, enhance transparency, and actively engage the public to address pressing environmental challenges.
2 Facilitate Technological Integration in Transition Economies: Empirical results suggest that economic complexity enhances environmental performance only beyond certain thresholds. Therefore, countries at a mid-stage of complexity should expedite the adoption of clean technologies. International collaboration via environmental agreements, foreign investment, and technology transfer can facilitate a more rapid transition across this threshold. These findings are consistent with several Sustainable Development Goals. Specifically, SDG 9 (Industry, Innovation, and Infrastructure) emphasizes the role of infrastructure and technological innovation in mitigating environmental impacts, particularly in developing countries.
3 Customize Renewable Energy Strategies According to Development Stage: Although renewable energy offers long-term advantages,

findings suggest that its environmental impact varies with different stages of development. Additionally, SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) underscore the importance of deploying renewable energy, improving energy efficiency, and implementing climate-conscious policies. Aligning national strategies with these SDGs can enhance environmental outcomes while supporting sustainable economic development.

4 Guarantee the Efficient Application of Environmental Technologies: Countries should avoid a uniform approach to prevent setbacks. Low-complexity economies require stricter enforcement to prevent reliance on polluting technologies, whereas high-complexity economies should prioritize monitoring, innovation, and regular impact assessments to achieve sustainable outcomes.
5 Invest in Education and Environmental Awareness: The positive relationship between the Human Development Index (HDI) and environmental performance, especially in developing countries, suggests that the expansion of educational programs and awareness initiatives can enhance human capital and encourage environmentally conscious actions, thus supporting long-term sustainability aims.
6 Landlocked countries (e.g., Armenia, Kazakhstan, Uzbekistan) can enhance energy security and reduce reliance on fossil fuels by strengthening regional trade agreements, developing sustainable transportation infrastructure, and investing in renewable energy sources such as wind and solar. Coastal countries (e.g., Bangladesh, Indonesia, Vietnam) should focus on climate change adaptation, disaster preparedness, and sustainable management of fisheries and coastal tourism.
7 Resource-abundant countries (e.g., China, Iran, Indonesia) can promote sustainable growth by diversifying their economies, investing in green technologies, and channeling resource revenues toward long-term environmental and economic objectives. Diversified economies (e.g., Japan, South Korea, Singapore) should emphasize clean technology innovation, strengthen environmental governance, and enhance international collaboration for sustainable resource management.

CRediT authorship contribution statement

Habibeh Salimi: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Azar Sheikhzeinoddin:** Writing – review & editing, Supervision, Investigation.

Declaration of competing interest

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

Appendix

Appendix Table 1
wt of indicators

Policy Objective	w_j	c_j	Issue Category	w_j	c_j	Indicator	w_j	c_j	Polarity
Climate Change	0.28	0.12	Mitigation	100 %	–	Projected emissions in 2050	0.121	0.69	–
						GHG trend adjusted by emissions per capita	0.123	0.70	+
						GHG trend adjusted by emissions Intensity	0.118	0.67	+
						Adjusted emissions growth rate for black carbon	0.167	0.95	–
						Adjusted emissions growth rate for nitrous oxide	0.093	0.53	–
						Adjusted emissions growth rate for F-gases	0.142	0.81	–
						Adjusted emissions growth rate for methane	0.108	0.61	–
						Adjusted emissions growth rate for carbon dioxide	0.124	0.70	–
Env. Health	0.343	0.15	Sanitation & Drinking Water	0.40	0.15	Unsafe drinking water	0.48	0.0006	–
						Unsafe sanitation	0.51	0.0007	–
			Air Quality	0.22	0.08	Anthropogenic PM2.5 exposure	0.09	0.56	–
						Household solid fuels	0.26	1.51	–
						Ozone exposure	0.08	0.48	–
						NOx exposure	0.18	1.03	–
						SO2 exposure	0.10	0.61	–
						CO exposure	0.11	0.65	–
						VOC exposure	0.14	0.79	–
			Heavy Metal	0.36	0.13	Lead exposure	100 %	–	–
Ecosystem Vitality	0.375	0.17	Agriculture	0.41	0.36	Sustainable Nitrogen Management Index	100 %	–	–
			Biodiversity & Habitat	0.41	0.36	Species Protection Index	0.53	0.10	+
						Red List Index	0.46	0.08	+
			Air Pollution	0.17	0.15	Adjusted emissions growth rate for sulfur dioxide	0.22	0.35	–
						Ozone exposure KBAs	0.24	0.37	–
						Ozone exposure croplands	0.21	0.33	–
						Adjusted emissions growth rate for nitrous oxides	0.31	0.49	–

Appendix Table 2
Calculated EPI Values for Selected Asian Countries (2000–2022)

Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Armenia	0.6708	0.6672	0.6390	0.6338	0.6312	0.6193	0.6122	0.6050	0.5970	0.6053	0.5981	0.6091	0.6072	0.6185	0.6342	0.6361	0.6327	0.6198	0.6058	0.5934	0.5842	0.5789	0.5623
Azerbaijan	0.6404	0.6613	0.6758	0.6758	0.6607	0.6513	0.6573	0.6588	0.6525	0.6596	0.6565	0.6598	0.6598	0.6674	0.6750	0.6739	0.6794	0.6765	0.6755	0.6669	0.6605	0.6508	0.6289
Bangladesh	0.4995	0.5090	0.5169	0.5286	0.5345	0.5284	0.5263	0.5285	0.5315	0.5300	0.5268	0.5271	0.5288	0.5402	0.5455	0.5470	0.5519	0.5473	0.5476	0.5391	0.5339	0.5262	0.5051
China	0.5140	0.5261	0.5324	0.5318	0.5230	0.5023	0.4938	0.4914	0.4872	0.4845	0.4753	0.4784	0.4846	0.4972	0.5217	0.5372	0.5562	0.5644	0.5850	0.5918	0.5986	0.5973	0.5750
Cyprus	0.5316	0.5503	0.5679	0.5801	0.5833	0.5907	0.5981	0.6082	0.6094	0.6125	0.6045	0.6064	0.6022	0.6081	0.6232	0.6404	0.6453	0.6432	0.6474	0.6433	0.6323	0.6189	0.5980
Georgia	0.6233	0.6409	0.6294	0.6089	0.5931	0.6096	0.5908	0.5747	0.5617	0.5479	0.5495	0.5601	0.5558	0.5686	0.5816	0.5875	0.5897	0.5848	0.5934	0.5918	0.5947	0.6000	0.5870
India	0.4469	0.4558	0.4644	0.4773	0.4784	0.4809	0.4793	0.4771	0.4687	0.4597	0.4460	0.4379	0.4307	0.4380	0.4491	0.4581	0.4710	0.4719	0.4794	0.4774	0.4805	0.4807	0.4621
Indonesia	0.5327	0.5422	0.5518	0.5603	0.5599	0.5600	0.5615	0.5613	0.5666	0.5613	0.5566	0.5438	0.5365	0.5474	0.5549	0.5577	0.5743	0.5775	0.5853	0.5797	0.5872	0.5785	0.5428
Iran	0.5293	0.5372	0.5455	0.5498	0.5465	0.5457	0.5457	0.5530	0.5531	0.5481	0.5410	0.5468	0.5483	0.5700	0.5827	0.5889	0.5975	0.5888	0.5864	0.5780	0.5688	0.5578	0.5350
Japan	0.6782	0.6895	0.7016	0.7185	0.7192	0.7114	0.7134	0.7157	0.7289	0.7343	0.7353	0.7301	0.7142	0.7105	0.7141	0.7175	0.7311	0.7338	0.7447	0.7456	0.7449	0.7375	0.7112
Jordan	0.5210	0.5324	0.5490	0.5634	0.5701	0.5622	0.5710	0.5737	0.5821	0.5835	0.5830	0.5846	0.5789	0.5911	0.5952	0.5875	0.5943	0.5905	0.6073	0.6123	0.6247	0.6271	0.6108
Kazakhstan	0.6217	0.6734	0.6763	0.6644	0.6346	0.6162	0.5940	0.5880	0.5811	0.5819	0.5671	0.5803	0.5894	0.6116	0.6340	0.6452	0.6604	0.6573	0.6595	0.6632	0.6644	0.6685	0.6514
Lebanon	0.5532	0.5704	0.5900	0.6034	0.6186	0.6293	0.6551	0.6704	0.6741	0.6547	0.6383	0.6220	0.5820	0.5644	0.5621	0.5531	0.5613	0.5690	0.5809	0.5820	0.5992	0.6215	0.6020
Malaysia	0.5421	0.5546	0.5721	0.5929	0.6013	0.6002	0.6061	0.6169	0.6189	0.6295	0.6315	0.6370	0.6448	0.6515	0.6516	0.6504	0.6587	0.6630	0.6683	0.6651	0.6706	0.6726	0.6611
Pakistan	0.4940	0.5025	0.5104	0.5149	0.5101	0.5083	0.5064	0.5056	0.5040	0.4990	0.4908	0.4969	0.4987	0.5085	0.5191	0.5223	0.5219	0.5117	0.5102	0.4981	0.4858	0.4755	0.4590
Philippines	0.5980	0.6124	0.6268	0.6508	0.6604	0.6620	0.6719	0.6721	0.6764	0.6761	0.6672	0.6608	0.6551	0.6512	0.6445	0.6365	0.6338	0.6199	0.6262	0.6133	0.6098	0.6134	0.5926
Russia	0.6318	0.6479	0.6615	0.6732	0.6715	0.6639	0.6622	0.6644	0.6707	0.6760	0.6707	0.6702	0.6572	0.6626	0.6715	0.6802	0.6895	0.6930	0.6898	0.6825	0.6770	0.6669	0.6494
Singapore	0.6000	0.6112	0.6341	0.6701	0.6886	0.7053	0.7164	0.7358	0.7355	0.7249	0.7127	0.6925	0.6781	0.6700	0.6669	0.6513	0.6714	0.6908	0.6874	0.6911	0.6725	0.6648	0.6460
South Korea	0.6119	0.6231	0.6282	0.6353	0.6418	0.6386	0.6356	0.6316	0.6484	0.6592	0.6585	0.6500	0.6356	0.6315	0.6312	0.6298	0.6345	0.6317	0.6381	0.6605	0.6670	0.6691	0.6562
Sri Lanka	0.5827	0.5903	0.5945	0.6041	0.6072	0.6021	0.6094	0.6175	0.6251	0.6339	0.6305	0.6247	0.6198	0.6317	0.6353	0.6286	0.6343	0.6319	0.6419	0.6443	0.6360	0.6353	0.6217
Thailand	0.6456	0.6611	0.6751	0.6914	0.6903	0.6803	0.6741	0.6654	0.6682	0.6637	0.6565	0.6612	0.6616	0.6698	0.6800	0.6847	0.6894	0.6872	0.6966	0.6955	0.6889	0.6877	0.6649
Turkiye	0.5949	0.6070	0.6193	0.6308	0.6436	0.6429	0.6414	0.6295	0.6254	0.6153	0.5941	0.5972	0.5913	0.5995	0.6137	0.6201	0.6241	0.6169	0.6257	0.6324	0.6360	0.6378	0.6229
United Arab Emirates	0.5028	0.5082	0.5158	0.5109	0.5014	0.4891	0.4910	0.4871	0.4788	0.4815	0.4713	0.4619	0.4629	0.4697	0.4918	0.4957	0.5062	0.5263	0.5433	0.5508	0.5558	0.5511	0.5297
Uzbekistan	0.6372	0.6328	0.6346	0.6415	0.6467	0.6572	0.6687	0.6810	0.6900	0.6994	0.6956	0.6845	0.6764	0.6757	0.6778	0.6812	0.6819	0.6743	0.6719	0.6690	0.6702	0.6591	0.6290
Viet Nam	0.5444	0.5518	0.5618	0.5712	0.5739	0.5781	0.5888	0.5948	0.5990	0.5979	0.5899	0.5950	0.6026	0.6147	0.6255	0.6170	0.6151	0.6089	0.6075	0.5845	0.5681	0.5600	0.5428
best	Japan	Japan	Japan	Japan	Japan	Japan	Singapore	Singapore	Singapore	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan
worst	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	India	Pakistan	Pakistan

Data availability

Data will be made available on request.

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