NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF BANKING AND FINANCE

THE ROLE OF ESG FACTORS AND ARTIFICIAL INTELLIGENCE IN IMPROVING ENVIRONMENTAL QUALITY: INSIGHT FROM FIVE LEADING INDUSTRIAL ROBOTICS INSTALLED ECONOMIES

M.Sc. THESIS

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APPROVAL

We certify that we have read the thesis submitted by **Peter Oluwasegun Igunnu** titled **"The role of ESG factors and artificial intelligence in improving environmental quality: Insight from five leading industrial robotics installed economies"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Educational Sciences.

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I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

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ABSTRACT

The Role of ESG Factors and Artificial Intelligence in Improving Environmental Quality: Insight from Five Leading Industrial Robotics Installed Economies.

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This study analyzes the influence of artificial intelligence (AI), environmental, social, and governance (ESG) metrics, economic development, technical innovation, and population on the environmental quality of the five leading nations in industrial robot installations from 2011 to 2022. Diverse econometric methodologies are used to examine these interactions, including the CIPS and CADF unit root tests for variable stationarity and the Pesaran and Yamagata (2008) test for slope heterogeneity. The RALS-EG cointegration tests are used to investigate long-term relationships among the variables, while the Driscoll-Kraay, Rogers, and White estimators are applied for linkage analysis. Furthermore, CS-ARDL and MMQR estimators are used to guarantee robustness. The results indicate that AI markedly degrades environmental quality, mostly due to heightened energy consumption and greenhouse gas emissions linked to AI-driven operations in industrial environments. Conversely, ESG measures are essential in alleviating environmental deterioration by fostering sustainable practices and enhancing corporate accountability. Economic development enhances environmental quality when integrated with sustainable policies and effective resource management. Technological innovation enhances environmental quality by increasing energy efficiency and decreasing emissions via new technology. Population dynamics enhance environmental quality by fostering knowledge and the implementation of sustainable practices; nonetheless, issues persist in reconciling resource demand with ecological conservation. The paper offers pragmatic policy suggestions for governments in the chosen countries to mitigate the detrimental impacts of AI on environmental quality while optimizing the advantages of ESG measures, economic development, technological innovation, and demographic changes. The research delineates avenues for future inquiries, highlighting the need to address the shortcomings identified in this study.

Keywords*:* Artificial intelligence, economic growth, technological innovation, population, environmental quality.

ÖZET

Çevresel Kalitenin Artırılmasında ESG Faktörleri
ve Yapay Zekânın Rolü: Beş Önde Gelen Endüstriyel Robot
Kurulumuna Sahip Ekonomiden İçgörüler

Igunnu, Peter Oluwasegun
Yüksek Lisans, Bankacılık ve Finans Bölümü
Ocak 2025, 76 sayfa

Bu çalışma, 2011'den 2022'ye kadar sanayi robot kurulumlarında lider beş ülkenin çevresel kalitesi üzerindeki yapay zeka (YZ), çevresel, sosyal ve yönetişim (ESG) metrikleri, ekonomik kalkınma, teknik yenilik ve nüfusun etkisini analiz etmektedir. Bu etkileşimleri incelemek için CIPS ve CADF birim kök testleri gibi değişken durağanlığını değerlendiren yöntemler ve eğim heterojenliğini test etmek için Pesaran ve Yamagata (2008) testi gibi çeşitli ekonometrik metodolojiler kullanılmaktadır. Değişkenler arasındaki uzun dönemli ilişkileri araştırmak için RALS-EG eşbütünleşme testleri uygulanmakta; Driscoll-Kraay, Rogers ve White tahmincileri ise bağ analizinde kullanılmaktadır. Ayrıca, CS-ARDL ve MMQR tahmincileri sağlamlık sağlamak amacıyla kullanılmaktadır. Sonuçlar, YZ'nin çevresel kaliteyi önemli ölçüde kötüleştirdiğini göstermektedir; bu durum, YZ ile yönlendirilen operasyonlarda artan enerji tüketimi ve sera gazı emisyonlarından kaynaklanmaktadır. Buna karşılık, ESG önlemleri sürdürülebilir uygulamaları teşvik ederek ve kurumsal hesap verebilirliği artırarak çevresel bozulmayı azaltmada hayati bir rol oynamaktadır. Ekonomik kalkınma, sürdürülebilir politikalar ve etkili kaynak yönetimi ile entegre edildiğinde çevresel kaliteyi artırmaktadır. Teknolojik yenilik, enerji verimliliğini artırarak ve yeni teknolojiler aracılığıyla emisyonları azaltarak çevresel kaliteyi artırmaktadır. Nüfus dinamikleri ise bilgi birikimi ve sürdürülebilir uygulamaların hayata geçirilmesini teşvik ederek çevresel kaliteyi iyileştirmektedir; ancak, kaynak talebi ile ekolojik koruma arasında denge sağlama konusunda sorunlar devam etmektedir. Makale, seçilen ülkelerde hükümetlere, YZ'nin çevresel kalite üzerindeki olumsuz etkilerini azaltırken ESG önlemleri, ekonomik kalkınma, teknolojik yenilik ve demografik değişimlerin avantajlarını optimize etmeleri için pratik politika önerileri sunmaktadır. Araştırma, bu çalışmada belirlenen eksikliklerin ele alınması gerekliliğini vurgulayarak gelecekteki incelemeler için yeni alanlar tanımlamaktadır.

Keywords: Yapay zeka, ekonomik büyüme, teknolojik inovasyon, nüfus, çevresel kalite.

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LIST OF ABBREVIATIONS

AFF	Affluence
AI	Artificial Intelligence
CGS	Corporate Governance Scores
CO_2 emissions	Carbon Emissions
EC	Energy Consumption
ESG	Environmental, Social, and Governance
ED	External Debt
EE	Energy Efficiency
EG	Economic Growth
EI	Environmental Innovation
EP	Energy Price
EPU	Economic Policy Uncertainty
ET	Environmental Tax
ETS	Emission Trading System
EQ	Environmental Quality
FA	Financial Accessibility
FD	Financial Development
FDI	Foreign Direct Investment
FF	Fossil Fuels
FG	Financial Globalization

FI	Fixed Asset Investment
FO	Foreign Ownership
FS	Firm Size
GE	Green Energy
GF	Green Finance
GMI	Green Management Innovation
GPI	Green Product Innovation
GT	Green Tax
GTI	Green Technological Innovation
HC	Human Capital
IF	Investment Freedom
INC	Income
IQ	Institutional Quality
LCF	Load Capacity Factor
ME	Methane Emissions
MPS	Manufacturing Production Structure
NE	Nuclear Energy
NRBV	Natural Resource-Based View
NRE	Non-Renewable Energy
PIS	Political Instability
POP	Population

R&D	Research and Development
RBV	Resource-Based View
RE	Renewable Energy
TI	Technological Innovation
TO	Trade Openness
TRI	Traditional Innovation
UA	Cultural Uncertainty Avoidance
URB	Urbanization.

CHAPTER 1

1 Introduction

1.1 Background of the study

In recent decades, climate change has emerged as a critical global issue, compelling governments across the spectrum, both developed and developing, to re-evaluate their energy policies and environmental legislation. Global environmental conferences have repeatedly advocated for coordinated actions to decrease CO_2 emissions (Petroleum, 2012). However, the environment remains under significant stress. The relentless pursuit of economic development has exacerbated pollutant emissions, sea-level rise, food and water insecurity, ocean acidification, extreme droughts, security risks, biodiversity loss, agricultural disruptions, rising healthcare costs, and resource depletion (Akpanke et al., 2024; Akram et al., 2020; Ali, Samour, et al., 2024; Faraji Abdolmaleki et al., 2023). These challenges have exacerbated ecological vulnerabilities, especially in emerging nations. Alarmingly, prevailing detrimental trends indicate that greenhouse gas concentrations will likely double from pre-industrial levels by 2035, possibly resulting in a global temperature increase above 2°C (Khalid & Özdeşer, 2021). Since CO_2 constitutes over 70% of the emissions of greenhouse gases, it plays a major role in environmental degradation. This issue has attracted the attention of economics, environmental scientists, politicians, and governments globally (Meo et al., 2023). The urgent challenge is to continuously improve ecological quality while facilitating a sustainable and low-carbon transition in economic and social advancement (Zhao et al., 2024). Achieving this dual goal requires innovative solutions that go beyond traditional approaches, since the intricacy and magnitude of environmental challenges need systemic and revolutionary measures.

In this regard, the integration of artificial intelligence (AI) with Environmental, Social, and Governance (ESG) approaches has surfaced as a viable technique for maintaining and enhancing environmental quality in response to these difficulties. Artificial intelligence, has proven to facilitate the advancements in green transition initiatives and has offered technical advances for the mitigation of environmental pollution (Luo et al., 2024). AI has two primary characteristics in macroeconomic functions: serving as an automation instrument and functioning as a multipurpose technology. AI, as an automation tool, decreases energy and resource utilization in standardized, repetitive manufacturing operations, hence improving efficiency, quality, and cost-effectiveness. AI, as a general-purpose technology, enhances many production sectors by its flexibility, ongoing innovation, and complementary uses, hence fostering economic development (Zhao et al., 2024). Current research emphasizes AI's capacity to enhance productivity while decreasing energy use, facilitating green industrial transformation, and mitigating carbon emissions (Liu et al., 2021). These technologies provide novel frameworks for reducing urban pollution and enabling green, low-carbon transitions (Luo & Feng, 2024). Researchers mostly concur that the incorporation of AI into economic systems may attain ecological sustainability while providing economic advantages (Bag & Pretorius, 2022; Li et al., 2022).

Simultaneously with the progress in artificial intelligence, the incorporation of ESG practices has surfaced as an important strategy for countries to maintain environmental integrity. The environmental aspect of ESG focuses on minimizing national carbon emissions, responsibly managing natural resources, and complying with international climate obligations (Qian & Liu, 2024). This aligns with AI-driven initiatives designed to reduce environmental pollution and promote sustainable transitions in national economies. Governments implementing ESG policies are progressively synchronizing their environmental initiatives with sustainability indicators, including carbon neutrality and biodiversity preservation, hence aiding global climate objectives (Alandejani & Al-Shaer, 2023).

ESG frameworks promote openness and accountability at the national level, especially in environmental reporting (Wong et al., 2021). Nations that integrate ESG principles into their policies are often mandated to report comprehensive statistics on greenhouse gas emissions, energy consumption, and water use (Singhania & Saini, 2022). This transparency not only bolsters public confidence but also stimulates innovation in policy-making since governments are motivated to implement cleaner technology and sustainable practices. The adoption of ESG policies in national government facilitates the allocation of green money to renewable energy projects, waste management initiatives, and conservation activities, hence aiding in the mitigation of environmental deterioration (Bank, 2020; Nasir & Ahmed, 2024). The governance component of ESG guarantees the constant incorporation of environmental goals into national policy formulation (Nõmmela & Kõrbe Kaare, 2022). Integrating sustainable development objectives into governance frameworks enables states to address environmental concerns more efficiently while striving for economic growth. Effective governance guarantees the establishment of regulatory frameworks that facilitate green transitions and uphold environmental norms, which are crucial for attaining long-term sustainability.

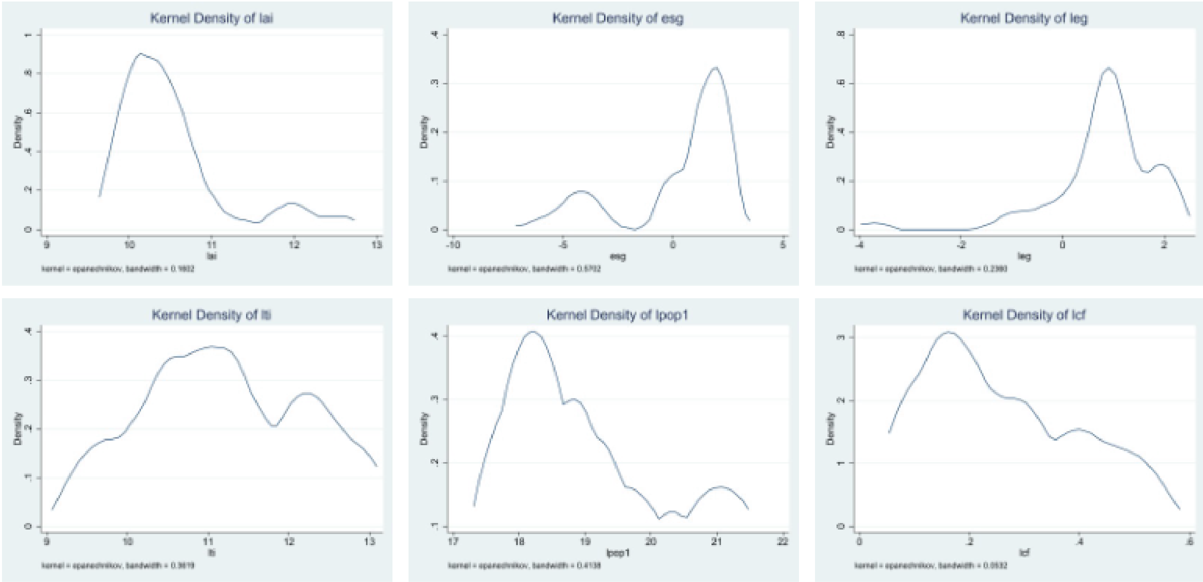

Figure 1: Kernel Density Chart

1.2 Problem statement

The foremost threat of our era is the changing climate due to its profound effects on environmental degradation. Human actions are accountable for its existence. Water levels are rising, storms are intensifying, food shortages are escalating, economic difficulties are mounting, and natural disasters are proliferating. Both domestic and international initiatives, together with policy adjustments, are essential to address climate change. Individuals, families, and communities all fulfill significant responsibilities. Today, even many who formerly denied climate change have acknowledged that human activities related to Carbon dioxide and other releases of greenhouse gases significantly contribute to environmental degradation. For the last 20 years, the threat presented by rapidly changing climates has garnered significant worldwide attention. Extensive studies on the impact of climate change on the global economy have been done since the mid-1990s. To alleviate the most severe consequences of global warming or climate change, many international organizations, including the UN, have been striving to establish legally binding agreements among states. Many nations have been exerting significant effort to mitigate the threats posed to the environment by human activity. Initiatives like CEFIM have been established to promote the development and use of renewable energy sources that are environmentally sustainable, while discouraging the use of non-renewable energy sources that are ecologically detrimental. Advocating for ecologically-focused technological breakthroughs is increasingly recognized as a crucial strategy in combating activities that deplete the environment, such as the emissions of CO2. Nevertheless, other are being held accountable for failing to implement significant measures to reduce the use of carbon-based fuels. It is essential for legislative bodies and individuals to collaborate on strategies for reconstruction. The potential for sustainable employment and innovations stimulates enhanced performance and excitement, since it will enable us to maintain competitiveness in the next years. The objective of this research is to reveal the effects of AI, ESG, EG, TI, and POP on the environmental quality of the five nations with the greatest number of deployed robots.

1.3 Motive of the investigation

The ongoing issues of flooding, erosion, food hunger, increasing sea levels, deforestation, altered rainfall patterns, and habitat degradation are all consequences of human activity, which are inversely connected to environmental quality. The extensive use of fossil fuels resulting from industrial growth significantly degrades environmental quality. Previous study studies indicate that AI has several beneficial effects on environmental sustainability and quality. Chen et al. (2022) indicate that AI substantially decreases carbon emissions by optimizing industrial frameworks, advancing green technology innovation, and augmenting information infrastructure. The aim of this study is to reveal the impact of AI, ESG, EG, TI, and POP on the environmental quality of the five nations with the biggest number of deployed robots: China, Germany, Japan, South Korea, and the United States. These economies are diligently striving to achieve green economies by investing in environmentally sustainable technology and enacting regulations.

1.4 Research questions

- What is the impact of artificial intelligence on environmental quality?
- To what extent does the ESG framework influence environmental quality?
- How does economic growth contribute to changes in environmental quality?
- What role does technological innovation play in shaping environmental quality?
- How significantly does population size affect the quality of the environment?

1.5 Hypothesis

This research employs two hypotheses: H_0, the null hypothesis, positing that the increase in AI, ESG, EG, TI, and POP does not significantly impact environmental quality in the chosen nations of analysis. The second hypothesis is H_1, representing the alternative hypothesis, which contrasts with the null hypothesis.

- H_0: AI has no notable effect on environmental quality.
- H_0: ESG framework does not meaningfully influence environmental quality.

- H_0: EG does not have a meaningful impact on environmental quality.
- H_0: TI does not noticeably affect environmental quality.
- H_0: POP does not meaningfully influence the quality of the environment.
- H_1: AI meaningfully impacts environmental quality.
- H_1: ESG framework noticeably affects environmental quality.
- H_1: EG has a meaningful influence on environmental quality.
- H_1: TI notably impacts environmental quality.
- H_1: POP meaningfully affects environmental quality.

1.6 Contributions of the investigation

Despite increasing evidence of AI's capacity to improve environmental results and the significance of ESG frameworks in fostering sustainability, considerable gaps persist. Initially, current research often examines AI or ESG in isolation, neglecting their synergistic effects on environmental quality. The particular function of industrial robots, a crucial application of AI in developed economies, remains little examined. Moreover, while much focus has been directed towards nations such as China and the United States, there is limited comparative study concerning the top five countries with the greatest industrial robot installations: "China, Germany, Japan, South Korea, and the USA". In addition to being top industrial robots installed countries, these nations exhibit varied economic frameworks, technical progress, and environmental regulations, rendering them ideal case studies for examining the interplay between AI, ESG, and EQ. Also, unlike previous study that utilize CO2 Emissions (metric tons per capita), PM2.5 Air Pollution (Micrograms per cubic meter), Adjusted Net Savings, Particulate Emission Damage (% of GNI) as proxy for environmental quality, this study utilize the load capacity factor (LCF) as a proxy for environmental quality, defined as $\left(\frac{\text{BIOCAPACITY (BC)}}{\text{ECOLOGICAL FOOTPRINT (EF)}}\right)$ from the Global Footprint Network (GFN)[1]. LCF evaluates a nation's ecological sustainability relative to a specified benchmark. Furthermore, it enables comprehensive research on environmental degradation (Ali, Samour, et al., 2024). In light of this backdrop, this study aims to investigate the impacts of AI and ESG, while also incorporating EG, TI, and POP as control variables, on EQ in the world's top five countries with the highest industrial robot installations (China, Germany, Japan, South Korea, and the

[1] For more information, kindly visit:
https://data.footprintnetwork.org/#/countryTrends?cn=5001&type=BCtot,EFCtot

United States). Our research contributes to the understanding of the impact of AI and ESG on the environmental quality in the five nations with the largest robot deployment. We enhance the literature by synthesizing the Resource-Based View (RBV) and the Natural Resource-Based View (NRBV) theory in our research, providing a solid theoretical framework. We use the newly developed Residual Augmented Least Squares-Engle and Granger (RALS-EG) co-integration approach to successfully tackle cointegration challenges. To enhance empirical precision, we use the econometric methodologies of Driscoll and Kraay (1998), White (1980), and Rogers (1993), addressing heteroscedasticity, autocorrelation, and cross-sectional dependence. Additionally, we use the Cross-Sectional Autoregressive Distributed Lag (CS-ARDL) and Method of Moments Quantile Regression (MMQR) methodologies to guarantee robust and dependable estimates. Our study offers practical insights for policymakers engaged in the green transformation of industrial sectors by concentrating on the five leading industrial economies.

1.7 Scope of the investigation.

This study pertains to the relationship between artificial intelligence, ESG, economic development, technical innovation, population, and environmental quality in the world's five leading nations for industrial robot installations: "China, Germany, Japan, South Korea, and the United States".

1.8 Definition of variables

Environmental quality (EQ) - A collection of environmental attributes affects humans and other living organisms. These attributes may be general or particular. It assesses the extent to which an ecosystem fulfills the requirements of humans and other species inhabiting the environment. The quality of the environment encompasses issues such as noise, water quality, air quality, and several other elements that may impact humans and other living organisms within the ecosystem.

Artificial intelligence (AI) - denotes systems that demonstrate intelligent behavior by assessing environmental data, including air, water, and soil quality, and autonomously executing actions or offering insights to enhance or preserve environmental sustainability. These systems use data-driven reasoning, predictive modeling, and adaptive learning to tackle issues such as pollution reduction, resource optimization, and climate change mitigation, therefore promoting healthier ecosystems and sustainable development.

Environmental, Social and Governance (ESG) - is a framework used to assess an organization's influence and efficacy in advancing environmental sustainability, encouraging social responsibility, and upholding ethical governance standards. In terms of environmental quality, ESG emphasizes the assessment and management of a company's role in diminishing pollution, preserving natural resources, alleviating climate change, and enhancing general ecological well-being via responsible practices and creative strategies.

Economic growth (EG) - refers to the increase in a nation's production capacity concerning its goods, assessed comparatively between two time periods while adjusting for inflation. An economy is seen to be increasing if the value of its goods increases, generating substantial income for businesses. Consequently, stock prices increase. This provides firms with capital to expand and hire extra personnel. Income increases due to the creation of many new work possibilities. With sufficient financial resources, consumers may acquire more products and services, resulting in accelerated growth. Every country seeks favorable GDP growth as a consequence of this.

Technological innovations (TI) - refer to the economic process by which new technologies are integrated into production and consumption. It involves identifying novel technical opportunities, coordinating the necessary people and financial resources to convert them into valuable goods and processes, and maintaining the essential operations. Technological advancements are crucial since they have significantly enhanced levels of life. Innovation is considered endogenous; that is, it reacts to fluctuations in demand and supply situations. A straightforward model differentiating between demand-pull and technology-push advances is introduced. Innovators sometimes fail to secure all the incremental economic advantages generated by their contributions, resulting in incentive failures known as 'the appropriability dilemma.' Innovative endeavors also include significant risks of technical failure and, notably, the misinterpretation of market needs. In response to these issues, mechanisms like the patent system and entities such as high-technology venture capital markets have developed.

Population (POP) - The aggregate of persons residing in a certain region, whose growth, distribution, and consumption behaviors substantially impact environmental quality. Population dynamics, including size, density, and migration, influence resource demand, waste production, and ecosystem health, consequently significantly impacting air and water quality, land use, and overall environmental sustainability.

1.9 Limitations of the investigation

This study has several drawbacks. The time range of data collected for this study is constrained (2011-2022) owing to unavailability. This study focuses only on the top five nations with the highest installation of industrial robots. This research study is quantitative and utilizes a secondary data source. This study ultimately used AI, ESG, EG, TI, and POP. Consequently, future researchers may use datasets with an expanded time range depending upon data availability. Furthermore, further study may conduct a comprehensive statistical analysis using time series methods to evaluate the differences among these countries. Additionally, prospective researchers may enhance this study model by including additional variables, such as research and development, environmental legislation, green energy investment, climate financing, green insurance, and green bonds. Ultimately, qualitative and quantitative research methodologies may be used concurrently in the future to bolster the findings and assertions of this study. The subsequent chapter, chapter two, concentrates on the literature research pertaining to the study's variables. The chapter includes both empirical and theoretical literature, along with the research gap between current inquiry and prior investigations. Chapter three outlines the methodological issues used in the empirical study. Chapter four concentrates on the outcomes and the analysis of the findings. Chapter five offers a brief but comprehensive analysis of the model's outputs, while chapter six addresses conclusions and suggestions.

CHAPTER 2

2 Literature Review

This chapter discusses the relevant prior research conducted by scholars worldwide, both empirically and theoretically. Furthermore, Appendix A presents a summary of the existing literature.

2.1 Empirical Literature

2.1.1 AI and Environmental Quality

AI has been identified as a pivotal tool in addressing environmental challenges and optimizing load capacity factor (LCF). Chen et al. (2022), utilizing the Bartik method across 270 Chinese cities, demonstrated that AI considerably diminishes carbon emissions through the optimization of industrial frameworks, improving green technology innovation, and enhancing information infrastructure. These findings are complemented by Ding et al. (2024), who applied emissions savings estimation in the United States and projected that employing AI could decrease energy use and emission levels by 8–19%. Their study further suggested that combining AI with low-carbon policies and energy generation could amplify these benefits, achieving up to a 40% reduction in energy consumption. Likewise, the research by Chen and Jin (2023) reveals that the amalgamation of AI and green innovation may facilitate low-carbon growth inside China's industrial sector. Liu et al. (2022) used the STIRPAT model to examine the impact of artificial intelligence on carbon intensity within China's industrial sector. The research demonstrated that AI significantly decreases carbon intensity, exhibiting more pronounced impacts in labour- and technology-intensive sectors; nevertheless, the influence fluctuates according to industrial phases and policy durations.

Similarly, Akhter et al. (2024), through ARDL bounds testing in the United States, underscored AI's positive impact on LCF by improving financial accessibility and institutional quality. However, Gaur et al. (2023), employing a System of Systems (SoS) analysis, warned of AI's potential to contribute to emissions, especially through unsustainable AI model development. Such contrasting perspectives underscore the need for sustainability-focused AI deployment, as highlighted by Saggar and Nigam (2023), who argue that AI's application in energy-intensive industries could significantly reduce greenhouse gas emissions through innovative solutions beyond conventional methods.

2.1.2 ESG and Environmental Quality

The integration ESG factors into economic activities plays a critical role in influencing LCF, albeit with varied outcomes across different conditions. Alandejani and Al-Shaer (2023), utilizing ordinary least squares (OLS) regression across the USA, China, and the UK, found that economic policy uncertainty drives higher ESG engagement, which indirectly enhances environmental goals and reduces carbon emissions. This perspective aligns with Khalil et al. (2024), who, through fixed-effects panel regression in 10 Asian countries, demonstrated that ESG investments not only positively affect firm value but also improve environmental performance, thereby supporting LCF enhancement.

In contrast, Işık et al. (2024), using a CS-ARDL model in G7 nations, observed a complex dynamic where governance factors within ESG frameworks positively impact LCF, but economic components have adverse effects, potentially undermining environmental goals. Wang et al. (2022) also highlighted the role of ESG bond issuance in Korea, linking it to firm size, foreign ownership, and carbon trading, yet observed no significant stock market reaction to these instruments. These findings suggest that while ESG frameworks have substantial potential to improve LCF, their economic dimensions must be carefully managed to prevent adverse environmental implications. Furthermore, Sun et al. (2024), using the SEM-ANN approach investigated the impact of green tax and energy efficiency on ESG performance of Bangladesh. The study reveals that green tax policies and energy efficiency positively impact ESG performance, with green tax mediating this relationship

2.1.3 EG and Environmental Quality

EG is a fundamental driver of environmental and energy systems, with mixed impacts on LCF depending on energy use and policy structures. Dai et al. (2024), employing the cross-sectionally augmented ARDL model in ASEAN nations, found that higher income levels and green energy adoption significantly boost LCF, demonstrating the potential of sustainable growth policies. Similarly, Jahanger et al. (2024), utilizing MMQR in top SDG nations, established a positive association between EG and LCF, emphasizing that economic expansion can align with environmental sustainability when complemented by green innovations.

Conversely, studies like Raihan et al. (2023) in Mexico and Xu et al. (2022) in Brazil suggest that economic growth can undermine LCF when driven by fossil fuel dependency. Their findings highlight that EG, when coupled with non-renewable energy reliance, reduces LCF while exacerbating urbanization’s adverse effects on environmental quality. Akhter et al.

(2024) further underscore the role of financial accessibility and institutional quality in moderating EG's impact on LCF. In the same vein, the study of (Ali, Igunnu, et al., 2024) using RALS-EG cointegration and ARDL model discovered that economic growth and gas prices increase emissions long term, however, economic growth decreases emissions in the short term. Also, the study of Wang et al. (2024) reveals that EG reduces the impact of carbon emissions in the near term as well as in the long term.

2.1.4 TI and Environmental Quality

Technological innovation (TI) exerts a profound yet context-dependent influence on LCF, shaped by its interaction with energy policies and resource utilization. Jahanger et al. (2024), using MMQR in SDG-focused nations, revealed that while TI alone negatively impacts LCF, its integration with renewable energy significantly enhances LCF across all quantiles. Similarly, Ali et al. (2023), through Driscoll-Kraay estimations in MINT nations, highlighted that TI's reliance on non-renewable energy decreases LCF, underscoring the importance of prioritizing green compliance and research and development.

Aydin et al. (2024), employing regularized common correlated effects in 19 countries, demonstrated mixed outcomes where TI enhanced LCF in Germany but reduced it in Singapore, reflecting variations in energy policies and industrial contexts. Akhter et al. (2024) and Guloglu et al. (2023) further emphasize the interplay between TI, renewable energy adoption, and human capital in determining LCF outcomes. Similarly, Ali, Igunnu, et al. (2024) using the RALS-EG cointegration and ARDL model, it was discovered that technological innovation has a negative effect on carbon emissions in Pakistan. In the same vein, Lin and Ma (2022) the STIRPAT framework and ARDL techniques revealed that technical collaboration also reduces environmental pollution in the near term. Conversely, Mehmood et al. (2024) investigated the relevance of green industrial transformation in reducing the emission of carbon. using a Robust least-squares approach. The outcome of the study shows that FDI inflows, technological innovations and R&D investments increase emissions.

2.1.5 POP and Environmental Quality

Population dynamics significantly influence LCF by shaping environmental demands and resource utilization. Djedaiet et al. (2024), using PMG-ARDL across seven African oil-producing countries, revealed that population growth exacerbates environmental pressures, reducing LCF through increased demand for goods, services, and resource depletion. Similarly, Dai et al. (2024) identified population density as a critical factor in ASEAN nations, finding it contributes to environmental deterioration, further straining LCF.

However Liu et al. (2022), applying the STIRPAT model in China's industrial sector argued that the impact of population on LCF varies based on affluence, industrial development stages, and policy interventions. Their findings suggest that effective management of population growth through investment in green infrastructure and sustainable urban planning could mitigate its adverse effects. Moreover, Akhter et al. (2024) the ARDL bounds test, FMOLS, DOLS, and CCR were used to assess the impact of private investment in AI and financial globalization on load capacity factor: evidence from the United States. The outcomes reveal that urbanization reduces the load capacity factor in both the short and long run. Similarly, Guloglu et al. (2023) examined the factors influencing the load capacity factor in OECD nations and found that human capital, resource rent, and renewable energy enhance the load capacity factor, whereas urbanization adversely impacts environmental quality. Furthermore, Raihan et al. (2023) examined the dynamic effects of economic expansion, financial globalization, fossil fuels, renewable energy, and urbanization on the load capacity factor in Mexico. The outcomes of the study indicated that economic growth, fossil fuel consumption, and urbanization reduce Mexico's LCF, while renewable energy adoption and financial globalization have positive effects on LCF. However, the study Xu et al. (2022) revealed that urbanization has no effect on LCF in Brazil.

2.2 Research gap

Despite increasing evidence of AI's capacity to improve environmental results and the significance of ESG frameworks in fostering sustainability, considerable gaps persist. Initially, current research often examines AI or ESG in isolation, neglecting their synergistic effects on environmental quality. The particular function of industrial robots, a crucial application of AI in developed economies, remains little examined. Third, while much focus has been directed towards nations such as China and the United States, there is a limited comparative study concerning the top five countries with the greatest industrial robot installations: “China, Germany, Japan, South Korea, and the USA”. Given the circumstances, the present research seeks to examine the effects of AI, ESG, EG, TI and POP on EQ in the world's top 5 industrial robots installed countries (“China, Germany, Japan, South Korea and the United State”). Appendix B provide a pictorial presentation of the countries selected for the study.

2.3 Theoretical Review

This study examines the influence of AI and ESG initiatives on environmental quality using the theoretical lenses of the Resource-Based View (RBV) and the Natural Resource-Based View (NRBV). These theories provide a comprehensive framework for understanding how resources and capabilities contribute to sustainable performance and eco-innovation. The RBV, introduced by Barney (1991), posits that a firm's competitive advantage lies in its possession of valuable, rare, inimitable, and non-substitutable (VRIN) resources. In this context, AI is conceptualized as a technological resource that enables firms to optimize operations, improve decision-making, and enhance innovation. ESG strategies, on the other hand, represent organizational resources that guide firms in aligning with environmental, social, and governance standards, promoting ethical practices and sustainability. However, the RBV has faced criticism for its inability to fully address the challenges posed by dynamic external environments, particularly environmental constraints. As DeSarbo et al. (2005) argue, while the RBV emphasizes the strategic value of resources, it does not adequately explain how firms can deploy these resources to achieve a competitive advantage in the face of increasing environmental pressures. Building on the RBV, Hart (1995) introduced the NRBV, which integrates environmental concerns into the resource-based framework. The NRBV recognizes that firms can achieve sustainable competitive advantage by leveraging resources and capabilities that address environmental challenges. According to Hart (1995, 2005), the NRBV emphasizes long-term strategies, such as investing in sustainable technologies and developing green capabilities, to create value while minimizing environmental harm. The NRBV suggests that firms must focus on accumulating resources and managing capabilities with a forward-looking perspective, prioritizing sustainability over short-term profits. For instance, the integration of AI and ESG initiatives aligns with the NRBV by enabling firms to adopt eco-innovative practices, such as energy-efficient systems and predictive environmental monitoring. These techniques not only mitigate environmental effect but also augment competitiveness.

The RBV and NRBV provide complementary perspectives for analyzing the role of AI and ESG in improving environmental quality. While the RBV highlights the strategic value of AI and ESG as resources, the NRBV underscores the importance of addressing environmental constraints and leveraging green capabilities for long-term sustainability. Recent studies, such as Menguc and Ozanne (2005), Dangelico and Pujari (2010) and Hart and Dowell (2011), have demonstrated how these theories can be applied to eco-innovation and environmental strategies. This study extends these theoretical frameworks by exploring the combined impact of AI and ESG initiatives on environmental quality, contributing to the growing body of literature on sustainable resource management and eco-innovation.

2.4 Conceptual framework

A conceptual framework denotes a graphic illustrating the normal relationship between the dependent and independent variables. The framework encompasses several factors and incorporates predictions by considering assumptions on their interrelations. This structure is a tool used prior to doing research. Consequently, a conceptual framework serves as an analytical unit. Robust conceptual underpinnings facilitate the attainment of specific objectives. It serves as a conduit for the inquiry, facilitating visualization and execution of a task. It enumerates the relevant parameters for the investigation and demonstrates probable correlations among them. The dependent variable is environmental quality, whereas the independent indicators are artificial intelligence and environmental, social, and governance (ESG) factors.

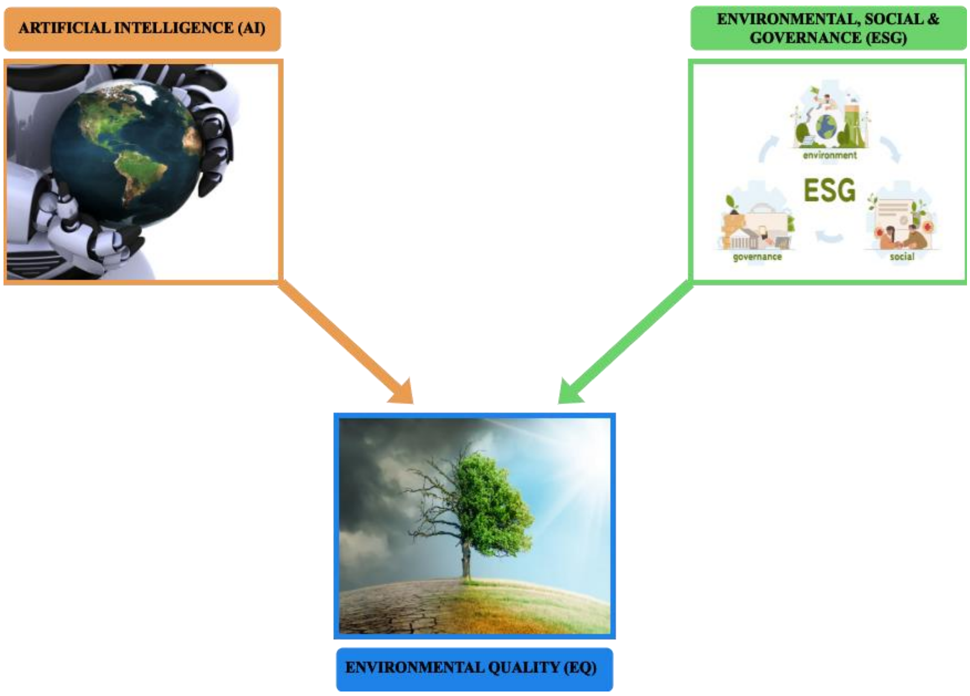

Figure 2: Theoretical Framework

CHAPTER 3

3 Methodology

3.1 Introduction

This chapter analyzes the impact of artificial intelligence, environmental, social, and governance metrics, economic growth, technological innovation, and population on environmental quality in the five foremost countries for industrial robot installations: China, Germany, Japan, South Korea, and the United States. Econometric methods are employed to determine the impact of independent variables on the dependent variable. The study's variables are accompanied with a succinct elucidation.

3.2 Data collection and sources

This study employs secondary data derived from existing literature. This facilitates comparisons between prior investigations and the current one. The analysis comprises five independent variables: artificial intelligence, environmental, social and governance metrics, economic growth, technical innovation, and population. The data parameters are sourced from the World Bank (WB), Global Network Footprint (GNF), and International Federation of Robotics (IFR). The inquiry employs panel data sourced from secondary materials to analyze the influence of the study's variables on environmental quality in the chosen nations. The investigation's sample size consists of data gathered from 2011 to 2022. These countries are selected based on two criteria. Initially, these countries have shown considerable progress and dedication in establishing a low-carbon future. Secondly, the accessibility of data on the selected economies is an additional aspect.

3.3 The Variables

The dependent variable is environmental quality. Various studies employ distinct proxies to assess this phenomenon (Ali, Igunnu, et al., 2024; Bashir et al., 2020; Costantiello & Leogrande, 2023; Khan et al., 2022; Saggar & Nigam, 2023) , however, we opted to utilize the load capacity factor (LCF) as a proxy for environmental quality, defined as $\left(\frac{\text{BIOCAPACITY(BC)}}{\text{ECOLOGICAL FOOTPRINT (EF)}}\right)$ from the Global Footprint Network (GFN)[2]. LCF evaluates a nation's ecological sustainability relative to a specified benchmark. Furthermore, it enables comprehensive research on environmental degradation (Ali, Samour, et al., 2024).

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[2] For more information, kindly visit:
https://data.footprintnetwork.org/#/countryTrends?cn=5001&type=BCtot,EFCtot

Incorporating LCF into environmental assessment is essential since it quantifies a nation's capacity to sustain its populace at existing living standards.

Additionally, this research employs two explanatory variables: Artificial Intelligence (AI) and the ESG index.

Recent empirical research identifies three primary methods for measuring AI. Total Factor Productivity (TFP) (Autor & Salomons, 2018) aims to quantify the levels of AI technology by assessing computational efficiency. Nonetheless, a shortcoming of this approach is its incapacity to differentiate whether technical progress originates from conventional technology or artificial intelligence, making it unsuitable for measuring AI. The alternative approach use the metric of "social fixed asset investment in information transmission, computer services, and software sectors" to evaluate AI advancement (McGaughey, 2022). This indicator largely signifies the expansion of the whole Information Technology (IT) sector, including both hardware and software components. Considering that AI represents a unique domain within the IT industry, this approach, albeit rational, has inherent limits. Moreover, while assessing AI capabilities across various nations, a frequently used metric is the inventory of industrial robots (Liu et al., 2020; Wang et al., 2023; Wang et al., 2024). This metric, derived from the (IFR, 2024), offers national-level statistics on robot stock inventories. Industrial robots are primarily divided into industrial and service robots, with the former accounting for the bulk of robotic energy usage (Iqbal & Khan, 2017). The sales volume of industrial robots serves as an indicator of the extent of artificial intelligence infrastructure (Zhang et al., 2021). Furthermore, since artificial intelligence comprises several technologies, it needs an appropriate medium for operation. The amalgamation of AI techniques with contemporary robotics has established industrial robots as the foremost embodiment of practical AI applications. Consequently, this research posits that the quantity of industrial robots serves as a more objective metric for assessing the extent of industrial AI.

Moreover, regarding ESG, various studies have employed distinct indicators (Alandejani & Al-Shaer, 2023; Khalil et al., 2024; Sun et al., 2024) , and in the absence of a universally recognized measure, we consequently develop an ESG index derived from the sixteen ESG indicators of the World Bank utilizing Principal Component Analysis (PCA) (Wold et al., 1987). The PCA is warranted due to the multitude of ESG measures and the sometimes-substantial correlation among them, complicating the identification of the most representative or relevant indicator for empirical analysis. The ESG index has a robust and positive correlation with all factors, as seen in Appendix C, indicating that the ESG index effectively elucidates all variables concurrently.

The first component of the ESG index has an eigenvalue of 9.0312, representing its variance. The first component accounts for 56.45% of the shared variance in the series, while the sixteenth component has an eigenvalue of 0.0065 and accounts for 0.04% of the variation. A number above one indicates that the component accounts for a larger proportion of variation than its expected share of the overall variance of the variables. Consequently, the first component is used in this case. An further measure of sample adequacy is the Kaiser–Meyer–Olkin (KMO) index, which assesses the relationship between partial correlations and correlations among variables. The use of PCA is warranted by a value over 0.50. Therefore, a KMO of 0.8028 validates the use of PCA. Table 1 presents essential attributes of the calculation of the ESG index.

Table 1: PCA and Eigenvectors.

Variables	Sample
PCA eigenvectors (highest)	9.0312
Proportion explained	0.5645
Kaiser-Meyer-Olkin	0.8028

Source: Author(s) compilation. Data retrieved from Stata.

Furthermore, to comprehensively assess the interaction between the explained and explanatory variables, three control variables are included to decrease variability from missing variables. Economic growth (EG) (Ali, Igunnu, et al., 2024; Djedaiet et al., 2024; Raihan et al., 2023), technological innovation (TI) (Aydin et al., 2024; Jahanger et al., 2024) and population (POP) (Chen et al., 2022; Liu et al., 2022). Additionally, Table 2 presents substantial details on the study variables.

Table 2: Variables information

Variables	Abb.	Measurement	Sources
		Explained Variable	
Environmental Quality	EQ	Derived by dividing biocapacity (per capita) by the ecological footprint (global hectares per capita)	Global Network Footprint[3]
		Explanatory Variables	
Artificial Intelligence	AI	Annual industrial robots installed	International Federation of Robotics[4]
Environment Social and Governance	ESG	Environment Social and Governance Index	Authors' Compilation
		Control Variables	
Economic Growth	EG	GDP growth (annual %)	WorldBank[5]

[3] For data, visit: https://data.footprintnetwork.org/#/countryTrends?cn=5001&type=BCtot,EFCtot
[4] For data, visit: https://ourworldindata.org/grapher/annual-industrial-robots-installed
[5] For data, visit: https://databank.worldbank.org/reports.aspx?source=World-Development-Indicators

Technological Innovation	TI	Patent applications, non-residents
Population	POP	Population, total

source: Author(s) Compilation

3.4 Estimation Techniques

The model of this study is presented below:

$$lnEQ_{it} = \beta_0 + \beta_1 lnAI_{it} + \beta_2 ESG_{it} + Control\ Variables_{it} + \xi_{it}$$

Equation 1

In the model above, environmental quality is represented by EQ_{it}; artificial intelligence is represented by AI_{it}; environmental, social and governance is represented by ESG_{it}. Moreover, β_0 represents the intercept, while β_1 and β_2 the coefficients of the variables Also, i, t and ξ denote the countries and the study period (2011–2022), and the error term, respectively. Furthermore, after incorporating the control variables, into equation (1), we derived at the equation below.

$$lnEQ_{it} = \beta_0 + \beta_1 lnAI_{it} + \beta_2 ESG_{it} + \beta_3 lnEG_{it} + \beta_4 lnTI_{it} + \beta_5 lnPOP_{it} + \xi_{it}$$

Equation 2

In the equation above, economic growth is represented by EG_{it}; technological innovation is represented by TI_{it}; while population is represented by POP_{it}.

3.4.1 Cross-sectional estimations

We evaluated cross-sectional dependence using the Cross-Sectional Dependence (CSD) estimator. This method assists in ascertaining the appropriate use of either the first or second order unit root test. If CSD is not evaluated, the results may be prejudiced and unreliable instead of resilient and trustworthy (Ali & Seraj, 2022). The equation for CSD is as follows:

$$CSD = \left(\frac{\tau}{\mathbb{N}}\right)$$

Equation 3

In Eq. (3), τ and $\mathbb{N}$ denote time and cross-sectional units, respectively. The term ϕ is denoted as:

$$\phi = \left(\frac{2}{\mathbb{N}(\mathbb{N}-1)}\right)\sum_{i=1}^{\mathbb{N}-1}\sum_{j=i+1}^{\mathbb{N}} Q_{ij}$$

Equation 4

In Eq. (4), Q_{ij} is the coefficient correlation of the ADF residuals.

3.4.2 Unit root estimations

According to the results of the CSD test, the estimators for the first-generation unit root test are considered inappropriate. Consequently, we evaluated unit roots in the panel data using second-generation methods, namely CIPS and CADF, to provide more robust and accurate results. The mathematical formulations of these assessments are as follows:

$$\Delta \mathscr{Y}_{it} = \Delta\psi_{it} + \beta_i X_{it} + \sigma_{it} + \sum_{j=1}^{n} \vartheta_{ij} \Delta X_{i,t-j} + \xi_{it}$$

Equation 5

$$CIPS = \mathbb{N}^{-1} \sum_{I=1}^{\mathbb{N}} CADF_I$$

Equation 6

Where $\Delta\psi_{it}$, X_{it}, Δ, t, and ξ_{it} denote the intercept, factor, variance, time, and error term, respectively.

3.4.3 Slope homogeneity estimations

In panel data econometrics, when the weights of many nations differ, the analysis of slope heterogeneity is crucial. To evaluate the initial slope heterogeneity, we use the test proposed by Pesaran and Yamagata (2008), which examines the dispersion of the weighted slopes across all nations. This evaluation is broken down by the relevant test statistics outlined in Equations (7) and (8).

$$\hat{\Delta} = \sqrt{\mathrm{Z}} \left(\frac{\mathrm{Z}^{-1} \mathbb{S}\% - K}{\sqrt{2K}} \right)$$

Equation 7

$$\hat{\Delta}_{adj} = \sqrt{\mathrm{Z}} \left(\frac{\mathrm{Z}^{-1} \mathbb{S}\% - K}{\sqrt{\frac{2K(T-K-1)}{T+1}}} \right)$$

Equation 8

3.4.4 Co-integration estimations

Subsequently, informed by the outcomes of the CIPS and CADF stationary analysis, which reveal that the roots lie outside the unit circle, we utilized the RALS-EG methodology introduced by Lee et al. (2015) and the cointegration technique of Westerlund and Edgerton (2007) to ascertain the cointegration relationship between the dependent and independent variables. The RALS-EG test framework consists of two stages. Initially, unit root tests were conducted to assess the integration order of each variable. Consequently, the OLS regression equation was formulated.

$$\Upsilon_t = \Phi z_t + \upsilon_t$$

Equation 9

Afterwards, residuals $\hat{\upsilon}_t$ were obtained and an ADF test based on these residuals was carried out.

$$\Delta\hat{\upsilon}_t = \text{Ҡ}_0 + \text{Ҡ}_1\Delta\hat{\upsilon}_{t-1} + \sum_{i=1}^{n}\text{Ҡ}_{i+1}\Delta\hat{\upsilon}_{t-1} + \delta_t$$

Equation 10

Equation (10) indicates that if the error term deviates from a normal distribution, it yields valuable insights into non-normal residuals via increased moments of the residuals. The RALS methodology, proposed by Im and Schmidt (2008), may integrate high-moment information from non-normal errors inside linear model frameworks, effectively addressing non-normally distributed error components, hence enhancing its efficacy. Consequently, the EG approach introduced by Lee et al. (2015), enhanced the RALS technique and included a new term for assessing cointegration. This was accomplished via the second and third seconds of the residuals. Conventional cointegration testing produces these residuals. This equation extends Equation 10.

$$\hat{\alpha}_t = \jmath(\hat{\delta}_t) - \hat{\text{Z}}_t - \hat{\delta}_t\hat{\text{E}}_t \quad t = 1, 2, 3, \ldots\ldots, T$$

Here, $\hat{\delta}_t$ represents the residuals generated from Equation 6 and

$$\jmath(\hat{\delta}_t) = \left[\hat{\delta}_t^{\,2}, \hat{\delta}_t^{\,3}\ \right], \quad \hat{\text{Z}} = \frac{1}{T}\sum\nolimits_{i=1}^{T}\jmath(\hat{\delta}_t) \ and\ \hat{\text{E}} = \frac{1}{T}\sum\nolimits_{i=1}^{T}\jmath'(\hat{\delta}_t),$$

The term for RALS procedure was given by Meng et al. (2017), as described.

$$\hat{\alpha}_t = \left[\hat{\delta}_t^{\,2} - a_2, \hat{\delta}_t^{\,3} - a_3 - 3a_2\,\hat{\delta}_t\right]$$

Equation 11

Where $a_j = T^{-1} \sum_{i=1}^{T} \hat{\delta}_t{}^j$. By substituting equation 11 into equation 10, we get the RALS cointegration regression. It is represented below:

$$\Delta\hat{v}_t = \text{Ҡ}_1 \Delta\hat{v}_{t-1} + \sum_{i=1}^{n} \text{Ҡ}_{i+1} \hat{v}_{t-1} + \hat{\alpha}_t \, y$$

Equation 12

Using ordinary t-statistics, the assumption of no cointegration relationship between the two series ($\text{Ҡ}_1 = 0$) can be tested for null hypothesis. The examined series ($\phi 1 = 0$) can be evaluated by employing standard t-statistics. The test statistic's asymptotic distribution can be expressed as

$$t^* \rightarrow \varrho . t + \sqrt{(1 - \varrho^2)} . \Psi$$

t stands for test statistics of EG test, while t^* represents test statistics of RALS-EG test. Ψ is a standard normal random variable and ϱ is correlation coefficient between residuals generated from equation (12) and Equation (10).

Subsequently, we examined the multicollinearity among explanatory variables using the Variance Inflation Factor (VIF) test. The model must not include highly correlated explanatory variables, since the presence of multicollinearity may result in biased model outcomes. Fourth, we used the Weak CD test to evaluate the weak cross-sectional dependency inside the model. We used two methods, namely Friedman (1937) and Pesaran (2015) for Weak Cross-Sectional Dependence (CD).

3.4.5 Driscoll-Kraay standard error approach

The Driscoll and Kraay econometric estimator, introduced by(Driscoll & Kraay, 1998) is the optimal approach for achieving robust findings from the SH, Weak CD, and cointegration test estimates. The Driscoll-Kraay standard error technique in panel data analysis is used to mitigate problems of heteroskedasticity, cross-sectional dependency, and autocorrelation. It has significant benefit when used on large datasets with cross-sectional and temporal relationships. The methodology includes adjustments for calculating standard errors amid autocorrelation and heteroskedasticity, employs nonparametric estimation for robust results across diverse conditions, and is particularly effective for extensive panels where temporal dimensions exceed cross-sectional dimensions. In accordance with previous research (Ali et al., 2023; Shah et al., 2021; Sultana & Rahman, 2024), we have used this technique, and the equation is shown below:

$$\gamma_{it} = \chi_{it} + \xi_{it}, i = 1, \dots\dots, N, t = 1, \dots\dots, T$$

Equation 13

The explained variable, denoted as γ_{it} represents the EQ. The explanatory variables, denoted as χ_{it} includes AI, ESG, EG, TI and POP. To ensure the reliability of the Driscoll and Kraay estimator, we used the methods proposed by White (1980) and Rogers (1993). Moreover, we employed the CS-ARDL and MMQR estimators to validate the robustness of the Driscoll and Kraay results.

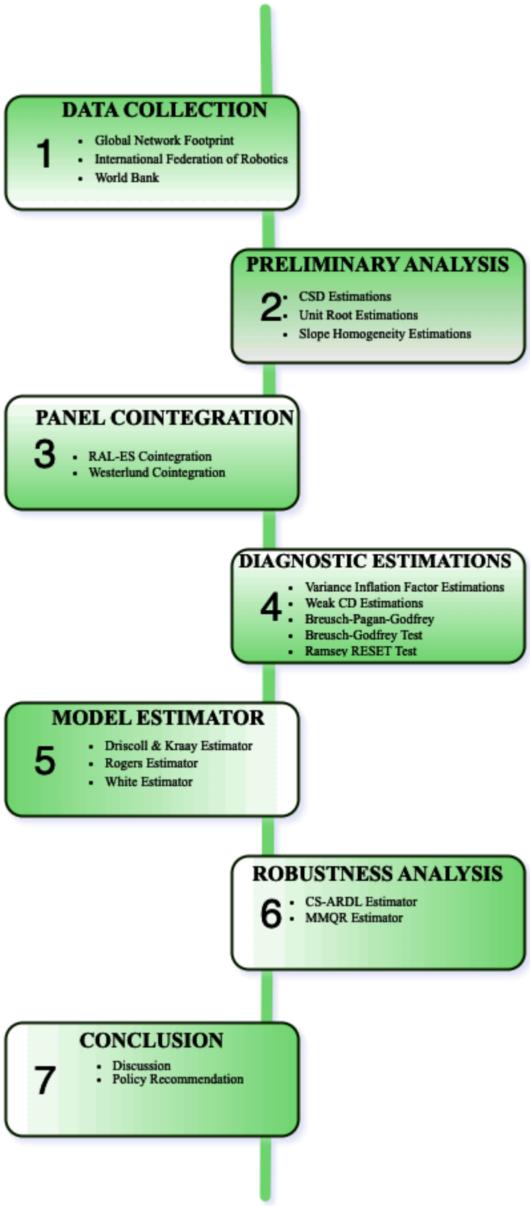

Figure 3: Methodological Flow

CHAPTER 4

4 Findings and Discussion

4.1 Introduction

This chapter outlines the results of the several econometric methodologies used in the data analysis. This chapter presents and interprets the findings of each tool outlined in Chapter 3. This analysis reveals the influence of artificial intelligence (AI), environmental, social, and governance (ESG) factors, economic growth (EG), technological innovation (TI), and population (POP) on environmental quality from 2011 to 2022. This is accomplished by the use of the Driscoll-Kraay, Rogers, and White methodologies. Additionally, CS-ARDL and MMQR estimators are used for robustness analysis.

4.2 Preliminary Outcomes

Table 3 displays the results of the descriptive statistics. The EQ exhibits a mean of 0.259 and a low standard deviation of 0.134, signifying consistency around the mean. The interval from 0.107 to 0.530 illustrates the variability within the dataset. The AI exhibits a mean of 10.513 and a standard deviation of 0.657, indicating minimal variability around the mean. The interval from 9.798 to 12.578 illustrates the degree of variability in the data. The ESG has a mean of 0.284 and a standard deviation of 2.543, signifying considerable variability. The interval from -6.557 to 2.931 signifies a broad distribution of values. EG exhibits a mean of 0.828 and a standard deviation of 0.992, indicating moderate variability around the mean. The interval from -3.738 to 2.257 indicates considerable variability in the data. The mean of TI is 11.197, accompanied by a moderate standard deviation of 0.976, indicating a relatively low degree of variability. The interval from 9.430 to 12.726 illustrates the degree of variability within the data. POP exhibits a mean of 19.055 and a standard deviation of 1.178, signifying substantial variability around the mean. The interval from 17.726 to 21.069 illustrates the variability within the dataset.

Table 3: Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
EQ	0.259	0.134	0.107	0.530
AI	10.513	0.657	9.798	12.578
ESG	0.284	2.543	-6.557	2.931
EG	0.828	0.992	-3.738	2.257
TI	11.197	0.976	9.430	12.726

POP	19.055	1.178	17.726	21.069

Source: Author(s); data derived from EViews 17. EQ = Environmental Quality; AI = Artificial Intelligence; ESG = Environment Social and Governance; EG = Economic Growth; TI = Technological Innovation and POP = Population.

Moreover, Table 4. shows the outcomes of cross-sectional dependence, unit root and slope heterogeneity. The outcomes affirmed the presence of cross-sectional dependence in the data; however, the unit root outcomes are in mixed order, such as ESG and EG are stationary at level whereas, EQ, AI, TI and POP are stationary at 1st difference as shown by CIPS and CADF test. However, the SH outcomes affirmed the existence of the slope in the coefficients of tested variables.

Table 4: Cross-sectional dependence, unit root and slope heterogeneity estimations

	CD-test	Level			First Difference		
Variable	CD-test	CIPS	CADF	RALS-ADF	CIPS	CADF	RALS-ADF
EQ	0.40	-1.44	-1.441	2.805	-2.683	-2.683	5.664
AI	8.14	-2.021	-2.021	14.400	-3.096	-3.096	-
ESG	0.51	-2.613	-2.613	-1.756	-	-	-
EG	8.43	-3.29	-3.294	5.177	-	-	-
TI	9.22	-2.08	-2.082	13.214	-3.38	-3.38	-
POP	2.65	-2.21	-1.103	-14.264	-2.481	-2.481	-

Slope Heterogeneity				
$\hat{\Delta}$	P− value		$\hat{\Delta}$Adj	P− value
2.403	0.016		3.723	0.000

Source: Author(s); data derived from EViews 17. EQ = Environmental Quality; AI = Artificial Intelligence; ESG = Environment Social and Governance; EG = Economic Growth; TI = Technological Innovation and POP = Population; Note: "***, **, and * show the significance level at 1%, 5%, and 10%

The outcomes of the Variance Inflation Factor (VIF) test are presented in Table 5. The VIF values for all variables are less than 10, indicating no multicollinearity issues among the test variables in the model. Table 6 presents the results of the cross-sectional dependence (CD) tests. The CD statistic values for the Pesaran and Friedman weak CD tests are 1.666 and 17.862, respectively, which are significant at the 10% and 1% significance levels. These results indicate the presence of cross-sectional dependence in the panel data. Furthermore, Table 7 summarizes the findings related to heteroscedasticity and autocorrelation. The Breusch–Pagan test yields a χ^2 statistic of 5.43 with a p-value of 0.0198, suggesting evidence of heteroscedasticity in the dataset. Similarly, the Modified Wald test produces a χ^2 statistic of 191.21 with a p-value of 0.0000, further confirming the presence of heteroscedasticity. Additionally, the Wooldridge test for autocorrelation provides an F-statistic of 354.136 with a p-value of 0.0000, indicating the presence of serial correlation in the dataset.

Table 5: Multicollinearity outcomes

Variable	VIF	1/VIF
AI	1.95	0.512899
ESG	2.63	0.380475
EG	2.28	0.439309
TI	1.49	0.672408
POP	1.26	0.794237
Mean VIF	1.92	

Source: Author(s); data derived from EViews 17. EQ = Environmental Quality; AI = Artificial Intelligence; ESG = Environment Social and Governance; EG = Economic Growth; TI = Technological Innovation and POP = Population

Table 6: Weak CD outcomes

Method	CD Statistics	P-value
Pesaran's test	1.666	0.0957
Friedman's test	17.862	0.0013

Source: Authors compilation

Table 7: Heteroskedasticity and Autocorrelation Outcomes

Diagnostic tests	Results	P-value
Breusch–Pagan/Cook–Weisberg test for heteroskedasticity	5.43	0.0198
Modified Wald test for groupwise heteroskedasticity	191.21	0.0000
Wooldridge test for autocorrelation in panel data	354.136	0.0000

Source: Authors compilation

Additionally, the outcomes of the RALS-EG cointegration test are presented in Table 8. The results indicate that the EG test statistic is 0.9715, which is greater than the critical value of −3.98, while the RALS-EG test statistic is 7.1676, which is also greater than the critical value of −3.88. These findings suggest that neither test rejects the null hypothesis of no cointegration at the given significance level. Thus, both the RALS-EG and EG tests demonstrate that there is no long-term correlation between the dependent and independent variables.

Table 8: Cointegration Outcomes

Method	K	T-test	Rho
EG	0	0.9715	
RAL-EG	0	7.1676	0.196085

Note: *K* shows the optimum lag length found using recursive statistics; the 1%, 5% and 10% critical values for the EG test are −5.02, −4.32 and −3.98, respectively; the 1%, 5% and 10% critical values for the RALS-EG test are −4.80, −4.19 and −3.88, respectively.

4.3 Driscoll-Kraay, Roger's and White Estimations

The Driscoll-Kraay Estimator is used to ascertain the long-term relationship between the dependent and independent variables. The results are shown in Table 10. The results of the

White and Rogers estimators are shown in Table 9, which are used to validate the dependability of Driscoll-Kraay's results. The Driscoll-Kraay results reveal a noteworthy significant negative correlation between AI and environmental quality, with a coefficient of -0.135 and a p-value of 0.000. This research indicates that heightened AI deployment correlates with a deterioration in environmental quality, likely attributable to the energy-intensive and resource-dependent characteristics of AI technology. Although AI has the capacity to enhance resource efficiency, its environmental repercussions may surpass its advantages, especially in scenarios lacking the incorporation of sustainable practices in AI research. Furthermore, the results of the research correspond with those of Gaur et al. (2023), Ding et al. (2023) and Luan et al. (2022).

The correlation between ESG practices and environmental quality is positive, with a coefficient of 0.077; nevertheless, this impact is statistically negligible, as shown by a probability value of 0.715. This result suggests that while ESG frameworks are often intended to enhance sustainability, their effect on environmental quality may be restricted or vary across various areas or industries. Furthermore, the results correspond with the research conducted by Işık et al. (2024), Khalil et al. (2024) and Wang et al. (2022).

Economic growth has a modest but statistically significant positive impact on environmental quality, shown by a coefficient of 0.004 and a p-value of 0.036. This outcome indicates that economic growth may enhance environmental quality, maybe via investments in sustainable infrastructure or technology. Nevertheless, the extent of the impact is comparatively limited, suggesting that economic expansion by itself may not be enough to achieve substantial environmental enhancements without further policies or interventions. Moreover, the results correspond with the research conducted by Ali, Igunnu, et al. (2024), Djedaiet et al. (2024), Jahanger et al. (2024) and Khan et al. (2024).

Technological innovation significantly enhances environmental quality, shown by a coefficient of 0.038 and a probability value of 0.000. This highlights the essential function of technical progress in tackling environmental issues, since breakthroughs often result in enhanced resource efficiency, reduced emissions, and the creation of cleaner technology. Furthermore, the results of the research correspond with the findings of Ali, Igunnu, et al. (2024) and Aluko and Obalade (2020).

Population has a substantial positive correlation with environmental quality, shown by a coefficient of 0.221 and a p-value of 0.000. This discovery may indicate that greater populations contribute to heightened environmental awareness, activism, and the enactment of sustainability-oriented policy. Although population expansion is often linked to environmental deterioration, this outcome indicates that population dynamics may also have a beneficial impact under some circumstances, particularly when cultures exhibit heightened environmental awareness. Furthermore, the result corresponds with the research conducted by Chen et al. (2022) and Wang et al. (2024).

A comparison of the estimators by Rogers (1993) and White (1980) reveals that their outcomes closely align with those of the Driscoll-Kraay Estimator, hence enhancing the dependability of the regression findings. The findings indicate that environmental quality improves with rising ESG, economic expansion, technical innovation, and population, whereas it deteriorates with the advancement of artificial intelligence.

Table 9: Driscoll-Kraay, Rogers and White outcomes

Driscoll-Kraay estimator				
Variables	Coefficient	Std. Dev (SD)	t-Statistics	Probability
AI	-0.135	0.014	5.44	0.000
ESG	0.077	0.011	0.37	0.715
EG	0.004	0.016	2.39	0.036
TI	0.038	0.031	7.25	0.000
POP	0.221	0.411	-6.41	0.000
	Rogers estimator		White estimator	
Variables	Coefficient	Probability	Coefficient	Probability
AI	-0.135	0.005	-0.135	0.005
ESG	0.077	0.063	0.077	0.063
EG	0.004	0.947	0.004	0.947
TI	0.038	0.000	0.038	0.000
POP	0.221	0.023	0.221	0.023
$F_{Statistics}$ 113.77 Probability 0.000				
Root- MSE 0.093				

Source: Author(s); data derived from EViews 17. EQ = Environmental Quality; AI = Artificial Intelligence; ESG = Environment Social and Governance; EG = Economic Growth; TI = Technological Innovation and POP = Population

4.4 Robustness Estimations

The robustness check is conducted with CS-ARDL and MMQR estimators. The results of CS-ARDL shown in Table 10 indicate that the long-term coefficient of AI demonstrates a negative and significant correlation with environmental quality (coefficient = -0.13479, $p < 0.01$), suggesting that greater dependence on AI is associated with a decline in environmental quality over time. Similarly, in the medium run, AI persists in demonstrating a detrimental impact on environmental quality, although to a lesser extent (coefficient = -0.11046, $p < 0.10$). Moreover, based on MMQR results, AI adversely affects environmental outcomes (Q1 coefficient = -0.11615, $p < 0.01$), with this impact intensifying in higher quantiles (Q4 coefficient = -0.160687, $p < 0.01$). This suggests that the environmental deterioration linked to

AI is more significant in areas with superior environmental quality, perhaps owing to a greater dependence on resource-intensive AI technology in developed contexts.

In the long run, ESG practices have a positive and substantial correlation with environmental quality (coefficient = 0.077321, $p < 0.01$), indicating that the implementation of ESG frameworks improves environmental results. Furthermore, over the long term, ESG maintains a favorable and substantial impact (coefficient = 0.045876, $p < 0.05$), underscoring its essential function in enhancing environmental circumstances across both temporal dimensions. The results of MMQR indicate that ESG practices consistently have a positive and substantial effect across all quantiles, with their influence intensifying as environmental quality improves (Q1 coefficient = 0.058678, $p < 0.01$; Q4 coefficient = 0.103214, $p < 0.01$). This indicates that ESG frameworks are more efficacious in improving environmental quality in areas that already implement superior environmental norms, possibly attributable to enhanced institutional capacity and compliance with governance principles.

Furthermore, EG positively impacts environmental quality in the long run (coefficient = 0.037515, $p < 0.05$), but to a lesser extent. Notably, EG demonstrates no substantial short-term impact, indicating that its environmental advantages may only emerge over an extended timeframe. Furthermore, the results of MMQR indicate that EG has a favorable albeit less consistent effect. The effect is notable in Q1 (coefficient = 0.036293, $p < 0.10$) and Q2 (coefficient = 0.037447, $p < 0.10$), but it wanes at elevated quantiles, suggesting that the advantages of economic growth on environmental quality are more substantial in places with lower environmental development.

TI, however, does not have a statistically significant impact, suggesting that its contribution to enhancing environmental quality remains indeterminate over the long term. Nonetheless, TI (coefficient = 0.031624, $p < 0.10$) has a modest but substantial positive impact in the near term, perhaps signifying the nascent adoption of ecologically beneficial technology. TI, however, remains statistically insignificant over the majority of quantiles, indicating a restricted direct influence on environmental quality.

POP has a significant positive effect (coefficient = 0.221228, $p < 0.01$), underscoring its role in enhancing environmental quality, maybe indicative of the advantages of bigger populations embracing eco-friendly activities or policies. Similarly, in the short run, POP has a significant favorable effect (coefficient = 0.115394, $p < 0.01$). Moreover, MMQR results demonstrate that POP consistently has a substantial beneficial effect on environmental quality across all quantiles, with its influence intensifying in higher quantiles (Q1 coefficient = 0.170051, $p < 0.01$; Q4 coefficient = 0.29231, $p < 0.01$). This suggests that population expansion might favorably influence environmental results, especially in areas with superior environmental practices, perhaps via heightened environmental consciousness and policy implementation.

The error correction term (ECT = -1.06188, $p < 0.01$) is very substantial, highlighting the model's capacity to rectify disequilibrium and progress towards long-term equilibrium. Additionally, Figure 4 provides a graphical overview of the impact of each explanatory variables on the explained variable.

Table 10: CS-ARDL and MMQR robustness outcomes

CS-ARDL Outcomes				
Variables	Long term		Short term	
	Coefficient	Std. Dev (SD)	Coefficient	Std. Dev (SD)
AI	-0.13479***	0.025	-0.11046*	0.063
ESG	0.077321***	0.020	0.045876**	0.019
EG	0.037515**	0.018	-0.00086	0.021
TI	0.004082	0.022	0.031624*	0.019
POP	0.221228***	0.049	0.115394***	0.041
ECT			-1.06188***	0.112
MMQR Outcomes				
	Q_1	Q_2	Q_3	Q_4
AI	-0.11615*** (0.021)	-0.13377*** (0.022)	-0.14937*** (0.027)	-0.160687*** (0.036)
ESG	0.058678*** (0.019)	0.076295*** (0.020)	0.091903*** (0.025)	0.103214*** (0.033)
EG	0.036293* (0.021)	0.037447* (0.021)	0.03847 (0.027)	0.039212 (0.032)
TI	0.024463 (0.023)	0.005204 (0.024)	-0.01186 (0.030)	-0.024227 (0.040)
POP	0.170051*** (0.045)	0.218411*** (0.047)	0.261259*** (0.058)	0.29231*** (0.081)

Source: Author(s); data derived from EViews 17. EQ = Environmental Quality; AI = Artificial Intelligence; ESG = Environment Social and Governance; EG = Economic Growth; TI = Technological Innovation and POP = Population; Note: "***, **, and * show the significance level at 1%, 5%, and 10% and the standard errors are in parentheses

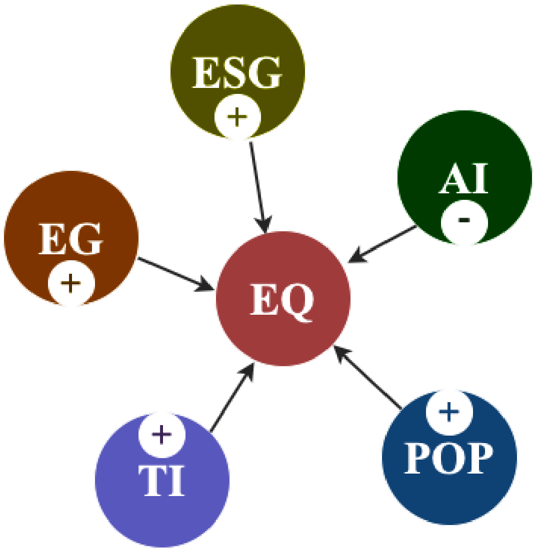

Figure 4: Overview of the impact of AI, ESG, EG, TI and POP on EQ.

CHAPTER 5

5 Discussion

The negative relationship between artificial intelligence (AI) and environmental quality that this study found highlights a significant conundrum that developed countries must deal with. On the one hand, artificial intelligence (AI) has become a game-changing technology that boosts economic competitiveness, optimizes industrial processes, and greatly increases productivity. However, because AI technologies are energy-intensive and significantly strain ecosystems, their rapid adoption has revealed environmental weaknesses. This dichotomy highlights a recurring problem: how to strike a balance between AI's industrial and economic advantages and the pressing need to lessen its negative environmental effects. Advanced computing infrastructure, including data centers, cloud computing platforms, and machine learning techniques, is essential to AI technology. In many nations, a large portion of the energy used by these systems still comes from fossil fuels. Therefore, in addition to increased energy use, AI's environmental impact also involves the depletion of natural resources and the production of greenhouse gas emissions. In developed countries like China and the US, where AI-driven procedures have been widely adopted to promote manufacturing and industrial innovation, these difficulties are especially noticeable. Despite being leaders in the deployment of technology, these nations' reliance on traditional energy sources makes the environmental effects of AI use worse. A striking illustration of this dynamic can be seen in China. A key component of the country's push for modernization and worldwide economic leadership has been the quick integration of AI into industrial operations. In sectors ranging from manufacturing to logistics, artificial intelligence (AI) technologies have proved crucial in increasing operational effectiveness, lowering production costs, and enabling predictive maintenance. But the ecology has paid a price for this advancement. According to Dong et al. (2024) and Zhang et al. (2024), despite the nation's aggressive renewable energy targets, the growing reliance on AI technologies has led to an increase in carbon emissions. The disparity is caused by the fact that China's energy grid is still mostly dependent on coal, even with large investments in renewable energy infrastructure. As a result, the electricity needed to run AI-driven operations frequently comes from non-renewable sources, which compromises the technology' potential environmental advantages. The size of China's industrial sector, which increases the environmental impact of AI adoption, further complicates this scenario. The continuous and significant energy inputs required by large industrial facilities using AI systems have not been adequately countered by the use of renewable energy sources. For instance, China's renewable energy capacity has increased significantly in recent years, but the adoption of AI and the energy requirements that go along with it have outpaced the country's shift to cleaner energy sources. This emphasizes the pressing need for methods to hasten the decarbonization of the energy grid and specific policies that give energy efficiency in AI applications first priority. Similar worries about the environmental costs of incorporating AI into industrial and manufacturing processes have surfaced in the US. Nepori (2024) emphasizes that although AI has greatly increased operational efficiency and productivity in the US manufacturing sector, these developments have come at the expense of higher energy consumption. This is especially noticeable in sectors like supply chain optimization, advanced robotics, and driverless cars that mostly rely on data-intensive operations. When these AI-driven systems are fuelled by non-renewable energy sources, the massive electricity consumption of the data centers that support them raises carbon emissions. Discussions over the sustainability of AI's broad adoption in the US have been triggered by the technology's energy-intensive nature. While the United States has made progress in increasing its capacity for renewable energy, the rate of expansion has not kept up with the increasing energy requirements of AI infrastructure. Furthermore, it is difficult to consistently adopt laws that encourage the use of green energy in AI operations due to the decentralized architecture of the US energy market. Nepori (2024) highlights the significance of implementing energy-efficient AI systems and legislative actions that encourage the use of renewable energy sources to power AI systems. In the absence of such steps, AI's carbon footprint may exceed its environmental advantages, jeopardizing more general sustainability objectives. The results of this study demonstrate the pressing need for calculated actions to reduce the hazards that artificial intelligence poses to the environment. Making energy-efficient AI research and development a top priority is one of the best strategies. The environmental impact of AI adoption could be considerably lessened by innovations like decentralized AI systems that use less energy, energy-optimized data center designs, and low-power machine learning techniques. In order to guarantee that sustainability is ingrained in the development and implementation of these technologies, governments and businesses must work together to create international standards for energy efficiency in AI applications. To solve the environmental issues raised by AI, policy changes are just as important as technical developments. For industries to switch to renewable energy, policymakers must provide incentives like green energy project subsidies or fines for over-reliance on fossil fuels. Since the environmental effects of AI adoption frequently cross national boundaries, international cooperation is also crucial. Initiatives for knowledge exchange and collaborative research can assist nations in creating and putting into practice best practices for the deployment of AI in a sustainable manner. The contribution of public awareness and education to the advancement of sustainable AI techniques is another crucial factor. By raising awareness of AI's negative environmental effects, stakeholders from a variety of industries can be persuaded to embrace more environmentally friendly methods. Customers can increase demand for AI-powered environmentally friendly goods and services, in addition to businesses and legislators. By combining the knowledge of the private sector with the financial and regulatory resources of governments, public-private partnerships can strengthen these initiatives even more.

Environmental, social, and governance (ESG) activities have a positive and statistically significant impact on environmental quality, which emphasizes how important sustainable business practices are to promoting environmental preservation while sustaining economic growth. In technologically sophisticated countries, where the incorporation of ESG frameworks has improved corporate governance and reduced environmental degradation, this association is especially noticeable. These countries show how ESG practices may balance the conflicting needs of environmental preservation and economic advancement by integrating sustainability concepts into corporate operations and governance frameworks. One prominent example of the effective application of ESG frameworks is Germany. The nation is well-known for its steadfast dedication to sustainability and has enacted strong laws to integrate environmental concerns into business and industrial operations. According to Ammermann and Ruf (2021), Germany's ESG efforts have been crucial in lowering emissions in a number of sectors while preserving economic expansion. These policies include required sustainability reporting for businesses, incentives for the use of renewable energy, and strict environmental restrictions. According to Meacci (2024), these regulations guarantee that German firms maintain their competitiveness in the worldwide market in addition to being in line with global environmental standards. The German experience demonstrates how ESG frameworks can be a useful instrument for striking a balance between environmental responsibility and corporate productivity. Other examples of how ESG principles might influence sustainability outcomes in technologically sophisticated countries are South Korea and Japan. Given the strategic importance of ESG practices in accomplishing long-term sustainability objectives, both nations have incorporated environmental issues into their corporate governance frameworks. According to Gunawan (2023), in order to incentivize companies to embrace eco-friendly practices, South Korea has put in place extensive ESG laws, such as carbon reduction targets and subsidies for green energy projects. Japan's attempts to integrate environmental sustainability into its corporate governance frameworks are also documented by Park et al. (2024). Adopting carbon neutrality targets and encouraging ecologically friendly developments in important industrial sectors are two examples of these initiatives. The efficacy of ESG practices in addressing environmental issues has been demonstrated by the observable improvements in environmental quality brought about by these policies taken together. The study's conclusions show that, especially in countries with highly developed technological capacities, the effective application of robust ESG frameworks can play a significant role in balancing environmental preservation with economic advancement. The capacity of ESG practices to tackle the environmental issues brought about by industrialization and economic growth highlights this relationship. Countries can accomplish two goals by incorporating sustainability considerations into company plans and governance structures: promoting economic growth and protecting the environment for next generations. ESG frameworks' capacity to encourage corporate accountability and transparency is another factor contributing to their efficacy in improving environmental quality. Businesses that follow ESG criteria are frequently compelled to report their sustainability and environmental performance, which fosters an accountable culture and promotes ongoing development. As stakeholders place a greater emphasis on sustainable practices when making investment decisions, this transparency not only helps the environment but also boosts investor trust. As a result, implementing ESG principles can help firms achieve substantial financial and reputational gains, which encourages their incorporation into corporate governance frameworks. Nevertheless, there are obstacles to overcome before ESG frameworks may be successfully implemented. Regulatory frameworks, cultural perspectives on sustainability, and economic development levels can all have an impact on how effective ESG practices are in different countries. For example, although South Korea, Japan, and Germany have made great progress in incorporating ESG principles, other countries may encounter challenges like insufficient legislative frameworks, restricted access to green technologies, and opposition from sectors that depend on non-renewable energy sources. A coordinated effort is needed to address these issues by promoting knowledge sharing among states, harmonizing ESG standards globally, and offering financial and technical assistance to underdeveloped nations. Innovations that promote sustainability have also been connected to the incorporation of ESG principles in technologically advanced countries. ESG frameworks that place a high priority on environmental stewardship frequently aid in the adoption of environmentally friendly technology, such as low-carbon innovations and energy-efficient production systems. This connection between technical innovation and ESG practices emphasizes even more how revolutionary ESG can be in advancing sustainability. For instance, improvements in energy-efficient industrial processes and renewable energy technology have resulted from South Korea's emphasis on green innovation, which is bolstered by its ESG regulations. Similarly, Japan's emphasis on incorporating ESG concepts into business operations has sparked advancements in environmentally friendly transportation and manufacturing technologies.

The study's contradictory findings about how Economic Growth (EG) affects environmental quality highlight the complex relationship between economic development and environmental quality in developed countries. The difficulty of balancing environmental sustainability with economic advancement is highlighted by the fact that some models show a statistically negligible association, while others show a minor positive benefit. These results highlight the dual nature of economic growth, whereby funds produced by development can help fund environmental projects but can also worsen environmental deterioration by increasing emissions and resource exploitation. Increased industrial activity, urbanization, and energy use are frequently associated with economic expansion, and these factors all exacerbate environmental problems. The need for economic growth has frequently come at the expense of environmental quality in countries like South Korea and Japan, especially in industries that rely significantly on fossil fuels. These economies, which are renowned for their highly developed technological capacities, struggle mightily to separate environmental damage from economic growth. For example, because of its reliance on non-renewable energy sources, Japan's industrial sector has historically contributed significantly to greenhouse gas emissions. The enormous expenses and infrastructure difficulties involved in modernizing current energy systems have hampered efforts to switch to renewable energy. In a similar vein, South Korea has had trouble balancing its goals for environmental sustainability and economic growth. The country's dependence on coal and other non-renewable energy sources has hindered the efficacy of its environmental policies, even if it is a pioneer in technological innovation and green technology development. In order to strike a balance between economic expansion and environmental preservation, South Korea continues to face significant challenges in integrating green development initiatives, such as the use of renewable energy and energy-efficient technologies. These countries' continued reliance on fossil fuels emphasizes the necessity of extensive legislative changes and clean energy expenditures in order to lessen the negative environmental effects of economic expansion. Economic growth's ability to supply funding for environmental projects is more proof of its dual character. Governments and businesses may invest in sustainable infrastructure, pollution prevention technologies, and renewable energy projects thanks to economic development. However, how much environmental factors are given priority in national development objectives will determine how beneficial these investments are. For instance, although both South Korea and Japan have put regulations in place to encourage sustainability, the rate of advancement has not been fast enough to offset the environmental costs of economic growth. This emphasizes how crucial it is to incorporate green development strategies that give equal weight to economic goals and environmental quality. In order to solve the environmental issues brought on by economic expansion in developed countries, green development methods are very important. These tactics entail implementing laws and procedures that minimize emissions, cut down on resource usage, and encourage the use of renewable energy sources. For example, a major step toward incorporating sustainability into its economic structure is Japan's pledge to become carbon neutral by 2050. Increased energy efficiency, increased capacity for renewable energy, and a shift to low-carbon technology are all part of this program. Similar to this, South Korea's Green New Deal seeks to promote sustainable economic growth by funding climate adaption, renewable energy, and green infrastructure initiatives. These programs show how green development strategies may balance environmental sustainability with economic advancement. However, governments, businesses, and communities must be committed to adopting sustainable practices for green development policies to be successful. By enacting laws that favor green growth, offering financial incentives for renewable energy projects, and encouraging the development of sustainable technology, policymakers can create a climate that is conducive to green growth. Furthermore, because environmental issues are global in scope, international cooperation is crucial. Countries may overcome the obstacles of putting green development methods into practice and achieving their sustainability goals by working together to share best practices, resources, and information.

As a key factor in enhancing environmental quality, technological innovation (TI) has demonstrated its indispensability in promoting sustainability in developed countries. TI's potential to transform waste management technologies, manufacturing procedures, and energy systems gives it the ability to tackle environmental issues. In addition to being a tool for reducing emissions, TI has become a key component of sustainable economic growth for major industrial powers like China, Japan, South Korea, and Germany. When it comes to using technical innovation to accomplish environmental goals, Germany is a global leader. Innovation may revolutionize energy systems, as seen by the nation's dedication to renewable energy, which is embodied in its "Energiewende" (energy transition) policy. Germany has made great strides in wind and solar power technologies, as well as energy storage systems that improve grid efficiency, by making large investments in research and development (R&D). Additionally, German firms have been able to minimize waste and maximize resource utilization because to advancements in production processes, such as the implementation of Industry 4.0 principles. These developments in technology highlight Germany's capacity to incorporate environmental sustainability into its industrial structure, establishing a standard for green innovation around the world. In a similar vein, Japan has shown how revolutionary TI can be when it comes to solving environmental issues. The nation's technological developments in waste management and energy efficiency have played a key role in cutting emissions and advancing circular economy principles. Japan is committed to become carbon neutral by 2050, which is reflected in its focus on creating high-efficiency energy systems like hydrogen-based technology. Furthermore, Japan is now a leader in sustainable urban development thanks to advancements in waste management, such as sophisticated recycling technology and waste-to-energy systems. These accomplishments demonstrate how TI can help resource-intensive economies, especially those in highly populated areas, develop sustainable solutions. The focus placed by South Korea on investments in green technology serves as another evidence of TI's transformative potential in enhancing environmental quality. R&D in smart grid technology, electric vehicles, and renewable energy has been given top priority under the nation's Green New Deal program. South Korea hopes to become a global center for green technology and move away from reliance on fossil fuels by encouraging innovation in these fields. Energy-efficient technology, like sophisticated battery systems and low-carbon industrial processes, have developed more quickly thanks to government backing for startups and research institutes. These initiatives show how South Korea views TI as a crucial facilitator of both environmental preservation and sustainable economic growth. China's strategy for technical innovation, especially its attempts to control the world's renewable energy market, is a prime example of how TI may revolutionize environmental sustainability. The nation has made significant investments in wind and solar energy technology, becoming the top manufacturer of wind turbines and photovoltaic panels worldwide. In addition to increasing China's capacity for renewable energy, these developments have lowered the cost of renewable technologies globally, opening them up to underdeveloped countries. Furthermore, China's emphasis on smart city technology and electric car manufacturing highlights its dedication to incorporating TI into sustainable urban development. There are still issues, though, namely with how China's industrial operations affect the environment and how to fairly divide technology gains among different regions. The study's conclusions highlight how crucial it is to maintain R&D spending in order to support ecologically friendly industrial practices. By acting as a catalyst to separate economic expansion from environmental deterioration, technological innovation helps countries meet sustainability targets without sacrificing industrial output. For business executives, tackling the environmental issues of the twenty-first century requires the ongoing development of green technology, such as enhanced waste management systems, energy-efficient manufacturing techniques, and renewable energy systems. Furthermore, international cooperation in technical innovation is required due to the global character of environmental concerns. Countries can pool resources and expertise to speed up the development and implementation of green technologies through technology transfer procedures, cooperative R&D programs, and knowledge-sharing efforts. Collaborations between South Korea and China in the development of renewable energy or Germany and Japan in hydrogen energy research, for instance, demonstrate the potential of joint innovation to promote sustainability globally.

Finally, the positive relationship between population (POP) and environmental quality found in this study emphasizes how important demographic dynamics are when combined with successful policy measures. Implementing well-thought-out legislation and encouraging group environmental action can have a positive impact on the relationship between population expansion and increased environmental stress, which is frequently linked to increased resource consumption and waste generation. The examples of China and the United States offer strong proof that demographic variables can support sustainable development and environmental enhancements when appropriately used. The interaction of government policies, community involvement, and public knowledge has been crucial in the United States in reducing the environmental impact of its sizable population. With one of the largest populations in the world, the United States inevitably puts strain on ecosystems and natural resources. Nonetheless, the country's focus on grassroots environmental projects and public awareness campaigns has been crucial in improving the condition of the environment. Environmental responsibility has been promoted via community-driven initiatives including recycling campaigns, nearby conservation projects, and popular support for renewable energy. Government policies that promote sustainable practices, such as stronger environmental laws, financial assistance for environmental education, and incentives for the use of green energy, further support these initiatives. Together, these actions show how, with the help of sensible laws and group efforts, a sizable population may be used to promote environmental change rather than operate as a liability. Another compelling example of how population-centric programs can support environmental sustainability is China. China, the world's most populated nation, has a difficult time striking a balance between environmental protection and population expansion. However, the country has shown how effective coordinated efforts and well-timed policy changes can be in tackling environmental problems. China is committed to lowering its dependency on fossil fuels and decreasing pollution, as seen by its ambitious renewable energy projects, which include the construction of massive solar and wind energy installations. Public initiatives to educate the country's large population about sustainable practices and energy saving help to support these initiatives. Furthermore, China's emphasis on green infrastructure and urban design has made it possible to create environmentally friendly cities that incorporate sustainable waste management techniques, renewable energy sources, and effective transit systems. China has demonstrated via the use of its demographic strength that population increase may result in notable environmental gains when combined with creative policies and group efforts. The importance of education and public knowledge in influencing environmental outcomes is further shown by the positive association between population and environmental quality. Communities can be empowered to take proactive action by educating the public about the advantages of sustainable practices and the negative effects of environmental deterioration. Campaigns that encourage water conservation, trash reduction, and energy efficiency, for instance, can have a multiplier impact when people adopt eco-friendly habits that add up to larger gains. A new generation of environmentally conscious citizens who are better prepared to handle future issues can also be fostered by investments in environmental education. In order to maximize the beneficial impacts of population dynamics on environmental quality, policy measures are essential. The creation and application of laws that promote sustainable conduct and offer rewards for eco-friendly activities must be given top priority by governments. For example, municipal policies that support green spaces, energy-efficient housing, and public transit can lessen the negative environmental effects of urban population density. Similar to this, policies for rural development that prioritize natural resource management and sustainable agriculture can guarantee that population expansion in rural areas does not result in resource depletion or environmental deterioration. By coordinating certain policies with demographic patterns, countries can turn population expansion into a benefit for environmental sustainability. The beneficial effects of population dynamics on environmental quality can also be strengthened through international collaboration and knowledge exchange. Countries can handle the problems caused by population expansion while maximizing its possible advantages by working together to exchange best practices, technical advancements, and regulatory frameworks. For example, international advancement in environmental sustainability can be promoted by the sharing of knowledge on community-based conservation initiatives and renewable energy technology between countries such as the United States and China.

CHAPTER 6

6 Conclusion and Recommendations

6.1 Introduction

The study analyzes the relationship among artificial intelligence (AI), environmental, social and governance (ESG) criteria, economic growth (EG), technological innovation (TI), and population (POP) concerning the environmental quality of the five countries with the highest installation of industrial robots from 2011 to 2022. The inquiry utilizes econometric methods in data analysis to explore the relationship between the variables. This study utilizes CADF and CIPS second-generation unit root tests, as presented by Pesaran (2007), to assess the stationarity of the parameters examined. The research employs the slope heterogeneity tests developed by Pesaran and Yamagata (2008) to examine the problem of slope heterogeneity related to the data. The research utilizes the recently established RALS-EG cointegration tests to examine the long-term relationship between the variables under consideration. This is accomplished by the use of the Driscoll-Kraay, Rogers, and White methodologies. Additionally, CS-ARDL and MMQR estimators are used for robustness analysis.

6.2 Summary of the Conclusion

This research illustrates the complex interrelationships between Artificial Intelligence (AI), Environmental, Social, and Governance (ESG) practices, Economic Growth (EG), Technological Innovation (TI), and Population (POP) concerning environmental quality in industrialized countries. The study use sophisticated econometric techniques, including Driscoll-Kraay, White, Roger, CS-ARDL, and MMQR estimators, to demonstrate the potential and problems associated with attaining environmental sustainability.

The results indicate that AI technologies now exert a considerable environmental impact owing to their energy-intensive characteristics. Although AI presents prospects to improve efficiency and stimulate innovation, its extensive use without sustainable practices may intensify environmental deterioration. Conversely, ESG practices have significant, beneficial effects on environmental quality in both the short and long term, highlighting the need of integrating sustainability into business and industrial activities. The results on economic growth suggest that, while it leads to minor enhancements in environmental outcomes, it is inadequate for realizing significant changes without supplementary, focused initiatives. Technological innovation serves as a fundamental element for improving environmental quality. Investments in green technology and creative production processes are essential for alleviating the negative impacts of industrialization and fostering sustainable development. Furthermore, population dynamics significantly influence the extent to which increased environmental consciousness among expanding populations may catalyze collective efforts towards sustainability.

6.3 Recommendations and Policy Implications

The results of the study offer a precise framework for practical policy suggestions to address the relationship among economic growth, technical advancements, and environmental quality. The policies that follow build on these recommendations by highlighting how crucial cooperation, creativity, and flexible governance are to achieving sustainable development objectives.

Advocate for Sustainable AI Technology

With AI's increasing use in industrial processes and its energy-intensive nature, it is critical to promote sustainable AI technology. Leaders in the public and corporate sectors should give top priority to research and development (R&D) projects aimed at developing AI systems that use less energy and emit fewer emissions. This could entail developing decentralized AI technologies that lessen the demand for large amounts of processing power, streamlining data center operations, and encouraging innovation in low-power machine learning algorithms. Another crucial step is to set environmental performance standards for AI systems. Industries can be held responsible for the environmental effects of their AI applications by establishing explicit guidelines for energy efficiency and emissions reduction. Furthermore, companies can be encouraged to connect their operations with sustainability objectives by utilizing subsidies, grants, and tax incentives to encourage the use of green technologies in AI-driven industries. Legislators might also establish certifications for AI systems that use less energy, giving companies a competitive edge and encouraging eco-friendly customer behavior.

Enhance ESG Integration

In order to connect corporate practices with sustainability goals, industries must enforce Environmental, Social, and Governance (ESG) adherence. Strong regulatory frameworks requiring ESG reporting and compliance across industries should be created by policymakers. To guarantee accountability and promote the broad adoption of sustainable practices, these frameworks should incorporate tools like tax incentives for businesses that satisfy ESG standards and penalties for non-compliance. Governments can aggressively promote the advantages of ESG integration beyond enforcement by offering case studies, guidelines, and teaching materials that show how ESG practices may lower risk, increase stakeholder trust, and boost profitability. Enhancing public-private partnerships is equally important. By exchanging knowledge, combining resources, and encouraging creativity, partnerships between governments, corporations, and non-governmental organizations can hasten the adoption of ESG principles. Governments and financial institutions, for example, can work together to create ESG-focused investment funds that incentivize businesses for their sustainability initiatives.

Promote Sustainable Economic Development

Policies that incorporate sustainability into growth strategies are necessary to decouple economic progress from environmental deterioration. Governments should prioritize the development of renewable energy and offer financial incentives, including tax rebates and feed-in tariffs, to hasten the switch to cleaner energy sources. Green infrastructure investments, such eco-friendly buildings, sustainable urban design, and energy-efficient transit systems, can further lessen environmental impacts while promoting economic expansion. National development plans should incorporate circular economy frameworks, which place a high priority on waste reduction, resource efficiency, and product lifetime management. Industries can be encouraged to invest in cleaner technology and lower emissions by putting carbon pricing mechanisms like carbon taxes or cap-and-trade schemes into place. By promoting innovation, these strategies not only boost the economy but also produce income that may be used to fund sustainability initiatives.

Expedite Technological Innovation

In order to solve environmental issues and advance sustainable practices, technological innovation must be accelerated. To keep innovation at the top of national agendas, governments should greatly boost funding for research and development in clean energy and sustainable technology. Creating innovation hubs that include scholars, business executives, and legislators can promote cross-sector cooperation and the quick creation of innovative solutions. These facilities might concentrate on topics including advanced recycling systems, carbon capture and storage (CCS) technology, and renewable energy storage. Fostering collaboration between academic institutions, commercial businesses, and governmental organizations can also aid in closing the gap between research and commercialization, guaranteeing the widespread adoption of sustainable innovations. International R&D cooperation, especially in the sharing of innovations and best practices, can hasten the world's shift to sustainability.

Enhance Public Awareness and Community Engagement

Building a sustainable culture and promoting grassroots environmental action depend heavily on public awareness and community involvement. School curricula, workplace training, and community activities should all incorporate educational programs that improve environmental literacy and encourage sustainable practices. By addressing important topics like waste management, energy conservation, and climate change mitigation, these programs can enable people to make wise decisions. Local efforts, including neighborhood-focused recycling programs and campaigns to promote the use of renewable energy, can take advantage of population shifts to bring about significant change. High-density metropolitan areas, for instance, can gain from energy-efficient housing developments and public transit programs, while rural areas can concentrate on renewable energy installations and sustainable agriculture. In order to allow communities to participate in the creation of policies and keep an eye on the execution of sustainability initiatives, governments should also invest in digital platforms that promote citizen participation in environmental decision-making.

Implement Comprehensive Monitoring Systems

To guarantee the efficacy of programs intended to improve environmental quality, strong monitoring systems must be established. The environmental impact of AI technologies, ESG practices, and other factors should be evaluated and monitored in real-time by these systems. Policymakers can receive precise and fast information from advanced data analytics and AI-powered monitoring technologies, allowing them to recognize new issues and modify their plans of action accordingly. Regular reviews of policy results can aid in improving strategies and guaranteeing that they continue to be in line with changing economic and environmental circumstances. Governments might, for example, put in place performance dashboards that monitor the advancement of important sustainability metrics like resource efficiency, emissions reductions, and the use of renewable energy. These dashboards' public accessibility can improve accountability and transparency, building stakeholder trust and promoting ongoing participation.

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Appendices

Appendix A: Synopsis of existing literature

Author(s)	Methodology	Country	Dependent Variable	Independent Variable	Main Findings
Akhter et al. (2024)	ARDL bounds test, FMOLS, DOLS, and CCR	United States	LCF	FA, AI, URB, and IQ	Financial accessibility, artificial intelligence innovation, and institutional quality favorably affect load capacity, but urbanization diminishes the load capacity factor in both the short and long term.
Alandejani and Al-Shaer (2023)	Ordinary Least Square (OLS) regression, with robust standard errors	USA, China, UK	ESG and CO_2 emissions	EPU, PIS, and UA	Economic uncertainty drives higher engagement in ESG and emission reduction targets; political instability increases social and environmental engagement, while risk-tolerant societies show better ESG performance. Profitable companies handle uncertainty better and invest in ESG.
Ali et al. (2023)	Driscoll-Kraay standard error estimator with fixed effects	MINT (Mexico, Indonesia, Nigeria, Turkey)	LCF	ED, RE, NRE, and TI	In MINT countries, long-term foreign debt, renewable energy, and access to clean energy enhance LCF, whereas non-renewable energy and technical innovation diminish LCF. The study suggests prioritizing research and development to promote innovation and enforce environmental compliance to reduce non-renewable energy impacts.
Ali, Igunnu, et al. (2024)	RALS-EG Cointegration, ARDL Model	Pakistan	CO_2 emissions	GF, EG, HC, EP and TI	Green finance, human capital, and oil prices reduce carbon emissions in the short and long term. Economic growth and gas prices increase emissions long term, while economic growth decreases emissions in the short term. Policies fostering green investments and resilience are recommended.
Aydin et al. (2024)	Regularized Common Correlated	19 Countries	LCF	IF, TI, RE and EG	Investment freedom decreases LCF in New Zealand and increases it in Latvia.

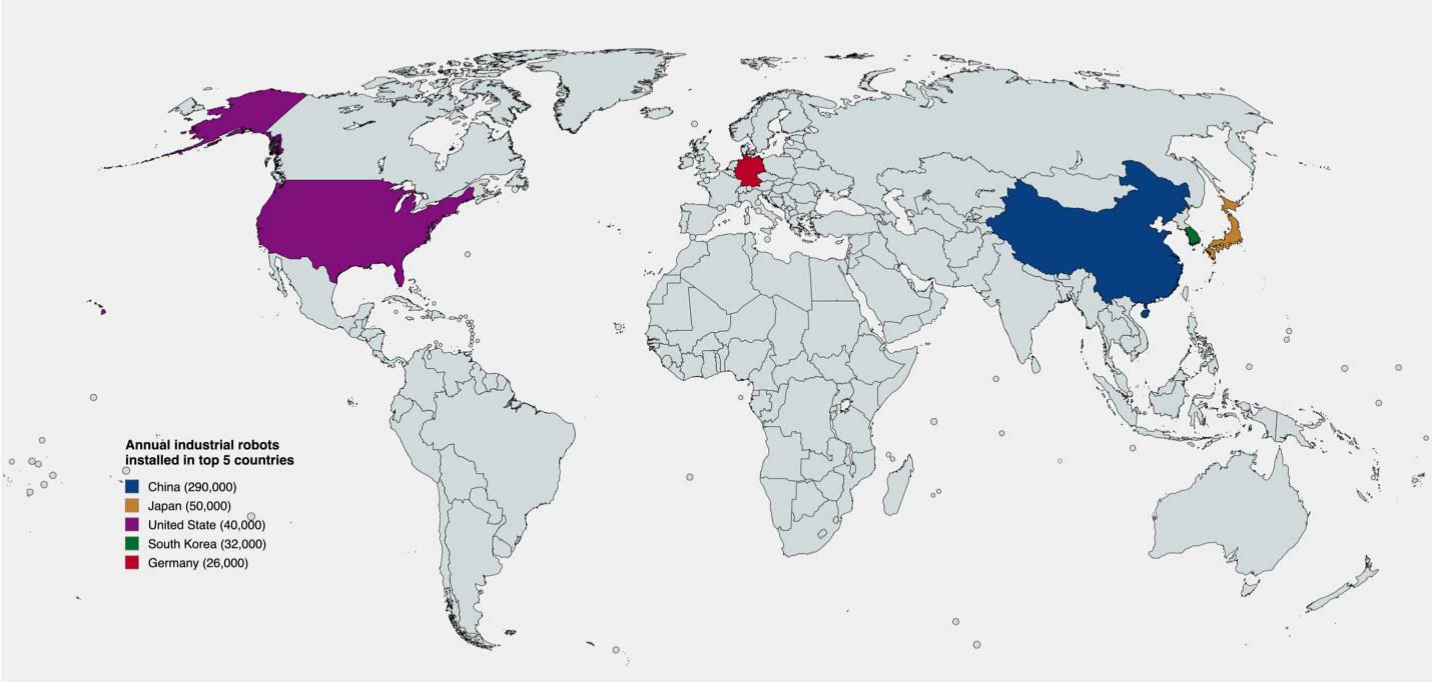
	Effects (rCCE) and Common Correlated Effects (CCE) estimators				Technological innovation decreases LCF for Singapore and increases it for Germany. Renewable energy increases LCF for the UK and Spain.
Chen et al. (2022)	Bartik method to quantify data	270 Chinese cities	CO_2 emissions	AI, FD, FI, and POP	Artificial intelligence exerts a substantial negative influence on carbon emission intensity. The impact of AI on carbon emission reduction is particularly pronounced in super and megacities, huge urban areas, and cities with superior infrastructure and modern technology. Artificial intelligence mitigates carbon emissions by optimizing industrial frameworks, strengthening informational infrastructure, and advancing green technological innovation.
Chen and Jin (2023)	Fixed-effects regression model	China	CO_2 emissions	AI, TI, GTI, GMI and GPI	The inhibiting effect of AI on carbon emissions is strengthened by the firms' green technological, management, and product innovation capabilities. The study provides evidence that the integration of AI and green innovation can promote low-carbon development in the manufacturing industry.
Costantiello and Leogrande (2023)	Fixed Effects, Random Effects and WLS-Weighted Least Squares	193 countries	CO_2 emissions	ME, R&D and RE	CO2 emissions are positively associated with methane emissions and R&D expenditures, negatively associated with renewable energy consumption and drought index
Dai et al. (2024)	Cross-sectionally augmented ARDL model	ASEAN Region	LCF	HC, GE, POP and EG	Higher income levels, human capital (HUC), and green energy stimulate load capacity factor (LCF) and environmental quality in ASEAN. Nonetheless, population density and economic globalization intensify environmental degradation.

					The study suggests policies to enhance environmental quality and achieve SDGs.
Ding et al. (2024)	Emissions savings estimation across scenarios	United States	CO_2 emissions	AI and EC	The implementation of artificial intelligence may decrease energy usage and carbon emissions by roughly 8% to 19% by 2050. Integrating artificial intelligence with energy policy and low-carbon power generation may decrease energy usage by 40% and carbon emissions by 90%.
Djedaiet et al. (2024)	PMG-ARDL for symmetric effects, PMG-NARDL for asymmetric effects, Westerlund cointegration test	African oil-producing OPEC countries (7 countries)	Environmental quality	EG, EC, EP and POP	The load capacity factor is adversely impacted by rises in oil prices, with short-term affects significantly outweighing long-term effects. An growth in population elevates the demand for products and services, hence exerting more strain on the environment. Moreover, population growth results in heightened detrimental activities towards the environment to satisfy fundamental demands through the depletion of natural resources.
Fareed et al. (2021)	Fourier quantile causality approach	Indonesia	LCF	INC, NRE and RE	Unidirectional causality exists from non-renewable energy usage to LCF across all quantiles. Income, export diversification, and renewable energy contribute to environmental quality at medium and upper quantiles. Renewable energy and export diversification enhance LCF, whereas income and non-renewable energy usage diminish LCF.
Gaur et al. (2023)	System of Systems (SoS) and network analysis	Not Specified	CO_2 emissions	AI	AI can combat climate change but contributes to carbon emissions; focus on creating sustainable AI models to minimize environmental impact.

Guloglu et al. (2023)	Quantile Common Correlated Effects Mean Group (QMG) estimator	OECD countries (26 countries)	LCF	HC, URB, RE	Human capital, resource rent, and renewable energy enhance the load capacity factor, however urbanization adversely impacts environmental quality. The research validates the U-shaped relationship between income and environmental quality, corroborating the load capacity curve concept. The findings underscore the significance of renewable energy and human capital in attaining Sustainable Development Goals, such as shifting to a low-carbon economy and mitigating water pollution.
Işık et al. (2024)	CS-ARDL model	G7 Nations	LCF	ECON-ESG	Governance factors positively affect LCF; economic factors negatively impact LCF. Environmental and social factors show no effect. ECON-ESG composite negatively affects LCF.
Jahanger et al. (2024)	MMQR and Dumitrescu & Hurlin	Top SDGs Nations	LCF	TI, ET, RE and EG	Technological innovation, environmental taxation, renewable energy, and globalization adversely affect LCF; economic growth positively influences LCF. The interplay between technological innovation and renewable energy enhances LCF across all quantiles.
Khalil et al. (2024)	Time fixed-effects panel regression.	10 Asian Countries	CO_2 emissions	ESG, CGS, TRI and EI	The findings of this study indicate that environmental performance significantly positively impacts the examined nations.
Liu et al. (2022)	STIRPAT model	Chinese industrial sector	CO_2 emissions	AI, POP, AFF, TI, FDI and Energy price	AI markedly decreases carbon intensity, with more pronounced effects in labor- and technology-intensive sectors; the impact fluctuates according to industrial phases and policy durations.
Raihan et al. (2023)	Autoregressive Distributed Lag (ARDL)	Mexico	LCF	EG, FG, FF, RE and URB	Growth in economic activity, fossil fuel use, and urbanization diminish Mexico's

	method, dynamic ordinary least squares (DOLS), fully modified least squares (FMOLS), and canonical cointegrating regression (CCR)				LCF, whilst the deployment of renewable energy and financial globalization exert beneficial effects on LCF. The results are consistent in both long-term and short-term dynamics. Policymakers must promote renewable energy, sustainable urban development, and eco-friendly technologies.
Saggar and Nigam (2023)	Theoretical framework and comparative analysis	Not Specified	GHG emissions	AI	The study indicates that employing AI could facilitate the identification and implementation of viable solutions for mitigating greenhouse gas emissions that might not have been achievable through traditional techniques.
Sun et al. (2024)	SEM-ANN Model	Bangladesh	ESG Performance	GT, EE	Green tax policies and energy efficiency enhance ESG performance, with green tax serving as a mediator in this relationship.
Wang et al. (2022)		Korea	ESG bond	FS, ESG committee, FO and ETS	The issuance of ESG bonds is positively correlated with firm size and foreign ownership interests. Companies having ESG committees and those participating in carbon trading are more inclined to issue ESG bonds. Minimal stock market response to ESG bonds in Korea.
Wang et al. (2024)	STIRPAT approach, mediation effect, and panel threshold techniques	69 countries	CO_2 emissions and energy transition	AI, TO, EG, and URB	AI promotes energy transition and reduces carbon emissions, especially in trade-open economies; the impact is subject to trade thresholds and country-specific factors.
Xu et al. (2022)	Bounds testing procedure for cointegration, ARDL method, and spectral causality test	Brazil	LCF	FG, URB, EG, RE and NRE	In Brazil, economic expansion and the utilization of both renewable and non-renewable energy diminish the load capacity factor, although urbanization exerts negligible influence. Financial globalization positively influences the load capacity

					factor. The research advocates for politicians to promote foreign investment to enhance environmental quality.
Yoon et al. (2020)	Multiregional input-output (MRIO) model and Structural decomposition analysis (SDA)	China, Japan, and Korea	CO_2 emissions	EC, TO and MPS	China is a net exporter of embodied carbon emissions to Japan and Korea, with its exports exhibiting greater carbon intensity than its imports. China's emissions are influenced by its production and trade framework, but Japan's and Korea's emissions are influenced by China's ultimate demand. Sectoral analysis identifies principal industries responsible for emissions.
Yun and Kang (2020)	Johansen Cointegration Test, ARDL Model	Korea, Japan, Germany	CO_2 emissions	NE, RE, FF	In Germany, nuclear and renewable energy sources have diminished CO2 emissions over the long term. In Korea, renewable energy, especially hydropower, has led to a rise in CO2 emissions. Japan exhibited no substantial effects aside from those related to fossil fuels. In the short term, nuclear energy in Korea and renewable energy in Germany diminished CO2 emissions, whereas alternative energy sources augmented emissions.



Appendix B: Top 5 industrial robots installed countries[6]

[6] For more details, visit: "https://ourworldindata.org/grapher/annual-industrial-robots-installed"

Appendix C: Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) ESG	1.000																
(2) E1	0.393	1.000															
(3) E2	-0.881	-0.206	1.000														
(4) E3	-0.791	-0.059	0.845	1.000													
(5) E4	0.387	0.018	-0.127	-0.064	1.000												
(6) E5	-0.880	-0.360	0.686	0.592	-0.519	1.000											
(7) S1	0.967	0.557	-0.807	-0.704	0.400	-0.867	1.000										
(8) S2	0.837	0.031	-0.713	-0.683	0.415	-0.702	0.739	1.000									
(9) S3	0.273	0.158	-0.173	-0.040	0.047	-0.217	0.199	0.180	1.000								
(10) S4	-0.282	-0.473	0.097	-0.003	-0.120	0.288	-0.293	-0.034	-0.831	1.000							
(11) S5	-0.952	-0.272	0.812	0.711	-0.558	0.898	-0.911	-0.852	-0.243	0.237	1.000						
(12) G1	-0.800	-0.362	0.642	0.595	-0.417	0.711	-0.801	-0.661	0.046	0.046	0.749	1.000					
(13) G2	-0.507	0.039	0.415	0.461	-0.113	0.379	-0.384	-0.640	-0.538	0.498	0.494	0.253	1.000				
(14) G3	0.852	0.600	-0.754	-0.660	0.242	-0.745	0.915	0.552	-0.010	-0.100	-0.760	-0.730	-0.087	1.000			
(15) G4	0.915	0.524	-0.867	-0.784	0.123	-0.748	0.935	0.662	0.092	-0.159	-0.789	-0.742	-0.303	0.929	1.000		
(16) G5	0.805	0.323	-0.612	-0.452	0.450	-0.683	0.748	0.772	0.574	-0.472	-0.785	-0.554	-0.553	0.543	0.620	1.000	
(17) G6	0.864	0.097	-0.925	-0.865	0.117	-0.697	0.777	0.725	0.177	-0.042	-0.784	-0.625	-0.364	0.760	0.850	0.585	1.000

Source: Author(s) compilation. Data retrieved from Stata

Appendix D: Turnitin Similarity Report

THESIS Peter

ORIGINALITY REPORT

15%	10%	12%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.mdpi.com Internet Source	1%
2	www.frontiersin.org Internet Source	1%
3	Mumtaz Ali, Ahmed Samour, Suhaib Ahmed Soomro, Waqar Khalid, Turgut Tursoy. "A step towards a sustainable environment in top-10 nuclear energy consumer countries: The role of financial globalization and nuclear energy", Nuclear Engineering and Technology, 2024 Publication	1%
4	link.springer.com Internet Source	1%
5	www.jescae.com Internet Source	1%
6	Submitted to Yakın Doğu Üniversitesi Student Paper	1%
7	Mumtaz Ali, Peter Oluwasegun Igunnu, Mehdi Seraj, Turgut Tursoy, Lydia Iradukunda. "Balancing green and growth: effect of green energy and moderating role of financial institutions and markets on economic growth in Mediterranean economies by advanced MMQR approach", Euro-Mediterranean Journal for Environmental Integration, 2025 Publication	<1%
8	www.ukais.org Internet Source	<1%
9	docs.neu.edu.tr Internet Source	<1%
10	Qiang Wang, Fuyu Zhang, Rongrong Li, Jiayi Sun. "Does artificial intelligence promote energy transition and curb carbon emissions?	<1%

Appendix E: Ethical Approval

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

09.12.2024

Dear Peter Oluwasegun Igunnu

Your project **"The Role of ESG Factors and Artificial Intelligence in Improving Environmental Quality: Insight From Five Leading Industrial Robotics Installed Economies."** has been evaluated. Since only secondary data will be used the project does not need to go through the ethics committee. You can start your research on the condition that you will use only secondary data.

Prof. Dr. Aşkın KİRAZ

The Coordinator of the Scientific Research Ethics Committee