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ARTIFICIAL INTELLIGENCE, CLIMATE RISK, GREEN INNOVATION, AND SUSTAINABLE DEVELOPMENT: THE INTERACTIVE EFFECTS OF INSTITUTIONAL QUALITY AND GENDER DIGITAL INCLUSION IN DEVELOPING ECONOMIES

A PANEL DATA ANALYSIS

Dr. Ahmad Noor[*1], **Dr. Tasneem Akhter**[2], **Humaira Noreen**[3]

[*1]*Rural Development, The University of Agriculture Peshawar*
[2]*Assistant Professor of Economics, Faculty of Management Sciences, University of Central Punjab, Lahore*
[3]*Department of Economics university of Peshawar, KPK*

[*1]ahmad0332an@gmail.com, [2]tasneem.akhter@ucp.edu.pk, [3]humairanoreen7@gmail.com

Corresponding Author: *
Dr. Ahmad Noor
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ABSTRACT
This study investigates the interactive effects of Artificial Intelligence (AI), climate risk, green innovation, institutional quality, and gender digital inclusion on sustainable development in developing economies. As countries accelerate digital transformation while confronting climate challenges, understanding how AI-driven technological progress interacts with governance quality and gender-inclusive digital access has become increasingly important. Using an unbalanced panel dataset covering 45 developing economies from 2005 to 2024, the study employs advanced panel econometric techniques including Cross-sectional Dependence (CD) tests, CIPS unit root tests, Panel ARDL, Cross-Sectionally Augmented ARDL (CS-ARDL), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), Augmented Mean Group (AMG), Common Correlated Effects Mean Group (CCEMG), Dynamic System GMM, Method of Moments Quantile Regression (MMQR), and Panel Quantile ARDL. The findings are expected to demonstrate that AI, green innovation, and institutional quality significantly improve sustainable development, while climate risk impedes environmental and economic performance. Furthermore, institutional quality and gender digital inclusion are hypothesized to moderate the effects of AI and green innovation, enhancing resilience and accelerating green economic transformation. The study contributes to the emerging literature on digital sustainability by integrating technological innovation, institutional governance, climate resilience, and gender-inclusive digitalization within a unified empirical framework.
Keywords: *Artificial Intelligence; Climate Risk; Green Innovation; Institutional Quality; Gender Digital Inclusion; Sustainable Development; Developing Economies; Panel Data Analysis.*

1. Introduction

1.1 Background

Artificial Intelligence (AI) has emerged as a transformative technology capable of enhancing productivity, environmental monitoring, energy efficiency, and climate adaptation. Simultaneously, developing economies face increasing climate-related risks that threaten economic growth, food security, and environmental sustainability. Green innovation offers pathways toward low-carbon development, yet its effectiveness depends heavily on institutional quality and equitable access to digital technologies.

Despite significant progress in digital transformation, the gender digital divide remains substantial across many developing countries, limiting women's access to digital technologies, AI-enabled services, and green innovation opportunities. Consequently, sustainable development depends not only on technological advancement but also on governance effectiveness and inclusive digital participation.

Sustainable development has become one of the most pressing global policy priorities as developing economies face the dual challenge of achieving economic growth while mitigating environmental degradation and adapting to climate change. Rapid industrialization, urbanization, and population growth have intensified greenhouse gas emissions, resource depletion, biodiversity loss, and climate-related disasters, threatening long-term economic prosperity and social welfare. These challenges are particularly severe in developing economies, where institutional weaknesses, limited technological capacity, and financial constraints hinder the implementation of effective environmental policies. Consequently, identifying innovative drivers of sustainable development has become an essential objective for policymakers, researchers, and international organizations.

Recent advances in Artificial Intelligence (AI) have transformed production systems, governance mechanisms, and environmental management worldwide. AI technologies—including machine learning, big data analytics, predictive modeling, and intelligent automation—offer unprecedented opportunities to optimize energy consumption, improve resource efficiency, enhance climate forecasting, monitor environmental degradation, and support evidence-based policymaking. By increasing productivity while reducing environmental externalities, AI has emerged as a key technological enabler of sustainable development. Nevertheless, the sustainability benefits of AI are not automatic and depend largely on the institutional environment, digital infrastructure, and inclusiveness of technological adoption across society.

Climate risk represents another critical determinant of sustainable development. Increasing frequencies of floods, droughts, extreme temperatures, cyclones, and other climate-related shocks impose substantial economic costs, reduce agricultural productivity, damage infrastructure, increase health expenditures, and exacerbate poverty and inequality. Developing countries are disproportionately vulnerable because of their heavy dependence on climate-sensitive sectors, inadequate adaptation capacity, and limited institutional resilience. Consequently, understanding how technological innovation can mitigate the adverse impacts of climate risk has become an important area of contemporary economic and environmental research.

Green innovation has gained considerable attention as a strategic mechanism for balancing economic growth with environmental sustainability. Green innovation encompasses environmentally friendly technologies, renewable energy development, eco-efficient production processes, sustainable manufacturing, waste recycling, carbon reduction technologies, and clean energy innovations. These innovations contribute to lower carbon emissions, improved energy efficiency, enhanced environmental quality, and increased competitiveness. Artificial intelligence is increasingly recognized as a catalyst for green innovation by facilitating research and development, optimizing industrial processes, accelerating technological diffusion, and improving environmental monitoring systems. Therefore, investigating the interconnected relationship among AI, green innovation, climate risk, and sustainable development is both theoretically and practically significant.

The effectiveness of these relationships, however, is strongly influenced by institutional quality. Strong institutions characterized by government effectiveness, regulatory quality, rule of law, control of corruption, political stability, and accountability provide the governance framework necessary for technological innovation, environmental regulation, and sustainable investment. High institutional quality improves policy implementation, reduces transaction costs, strengthens investor confidence, and encourages environmentally responsible business practices. Conversely, weak institutions may limit the effectiveness of AI technologies and green innovations by creating regulatory uncertainty, inadequate enforcement, and inefficient allocation of resources. Institutional quality may therefore act as a moderating factor that amplifies or weakens the influence of AI and green innovation on sustainable development.

An equally important but relatively underexplored dimension is gender digital inclusion. Although digital technologies are expanding rapidly across developing countries, substantial gender disparities remain in access to digital infrastructure, internet connectivity, digital skills, technological education, and participation in digital labor markets. Women's limited access to digital technologies restricts their ability to participate in innovation ecosystems, climate adaptation initiatives, entrepreneurship, and environmentally sustainable economic activities. Promoting gender digital inclusion not only advances gender equality but also enhances human capital, innovation capacity, labor productivity, and social resilience. Integrating women into the digital economy can strengthen the positive contribution of AI and green innovation to sustainable development by expanding the pool of skilled users, innovators, and decision-makers.

Despite the growing literature on artificial intelligence, climate change, environmental sustainability, and green innovation, existing empirical studies remain fragmented. Most previous research has examined the bilateral relationships between AI and environmental performance, climate risk and economic growth, green innovation and carbon emissions, or institutional quality and sustainable development. Very few studies have simultaneously investigate the dynamic interactions among AI, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development within a unified econometric framework. Furthermore, limited attention has been given to the moderating roles of institutional quality and gender digital inclusion in strengthening the effectiveness of AI-driven sustainability strategies in developing economies.

This study seeks to address these research gaps by examining the impact of Artificial Intelligence, Climate Risk, and Green Innovation on Sustainable Development in developing economies while incorporating Institutional Quality and Gender Digital Inclusion as interactive moderating variables. Using balanced panel data for selected developing countries over the period 2005–2024 (subject to data availability), the study employs advanced panel econometric techniques, including second-generation panel unit root tests, panel cointegration tests, Panel ARDL–Pooled Mean Group (PMG), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), Common Correlated Effects Mean Group (CCEMG), and Augmented Mean Group (AMG) estimators. These approaches allow for robust estimation in the presence of cross-sectional dependence, slope heterogeneity, and endogeneity.

The study contributes to the literature in several important ways. First, it develops a comprehensive conceptual framework integrating artificial intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development. Second, it empirically evaluates whether institutional quality and gender digital inclusion strengthen the effectiveness of AI and green innovation in promoting sustainability. Third, it provides robust empirical evidence using multiple long-run estimation techniques to ensure consistency and reliability of findings. Finally, the study offers policy recommendations that can assist governments, international organizations, and development partners in designing integrated strategies for digital transformation, climate resilience, gender equality, and sustainable economic development.

The findings are expected to provide important theoretical and policy insights regarding the role of emerging digital technologies in achieving the United Nations Sustainable Development Goals, particularly goals related to quality education, gender equality, industry and innovation, climate action, and sustainable economic growth. By highlighting the interactive roles of institutional quality and gender digital inclusion, the study aims to advance understanding of how developing economies can harness artificial intelligence and green innovation to build more resilient, inclusive, and environmentally sustainable development pathways.

1.1. Research Objectives

The study aims to:

1. Examine the impact of Artificial Intelligence on sustainable development.
2. Investigate the influence of climate risk on environmental sustainability.
3. Analyze the contribution of green innovation toward sustainable development.
4. Evaluate the role of institutional quality.
5. Examine whether gender digital inclusion moderates the relationships between AI, green innovation, and sustainable development.
6. Compare long-run and short-run relationships.

1.2. Research Questions

- Does Artificial Intelligence improve sustainable development?
- Does climate risk reduce environmental sustainability?
- Can green innovation offset climate-related risks?
- Does institutional quality strengthen AI-driven sustainability?
- Does gender digital inclusion promote green economic transformation?

2. Literature Review

2.1 Artificial Intelligence and Sustainable Development

Vinuesa et al. (2020) conducted the seminal global assessment of AI and the SDGs and found that AI can enable progress in 134 SDG targets while potentially inhibiting 59 targets if governance is weak. The study established AI as a transformative but governance-dependent driver of sustainable development.

Singh et al. (2024) reviewed AI applications across economic, environmental, and social dimensions and concluded that AI improves resource efficiency, environmental monitoring, and development outcomes, thereby accelerating SDG achievement.

Maghsoudi et al. (2025) emphasized that AI contributes to sustainability only when supported by inclusive governance and equitable policy frameworks, highlighting the importance of institutional arrangements.

Costa et al. (2025) showed through AI-patent semantic analysis that AI technologies are increasingly oriented toward SDG-related innovation, especially climate action, sustainable cities, and industrial innovation.

Leal Filho et al. (2026) synthesized recent evidence and argued that AI-based innovation has become a strategic instrument for achieving multiple SDGs, particularly environmental and urban sustainability goals.

2.2 Climate Risk and Sustainable Development

Sirmacek et al. (2022) extended the AI–SDG framework to climate action and demonstrated that AI enhances climate-risk forecasting, disaster management, and resilience planning, which are critical for sustainable development under increasing climate shocks.

Vinuesa et al. (2020) further argued that AI-enabled climate adaptation technologies can strengthen SDG 13 (Climate Action) by improving predictive capacity and environmental decision-making.

Năstasă et al. (2024) reviewed post-pandemic AI–sustainability research and found that climate resilience and environmental risk management have become central applications of AI in developing and emerging economies.

2.3 Green Innovation and Environmental Sustainability

Mansour et al. (2025) examined AI capability and green innovation efficiency and found that firms with stronger AI capabilities generate significantly higher green innovation outcomes, especially under stronger ESG governance structures.

Ridwan et al. (2026) showed that AI-driven innovation reduces ecological pressure by improving energy efficiency and environmental performance, confirming AI's role as a catalyst for green transformation.

Costa et al. (2025) also identified a growing concentration of AI patents in renewable energy, environmental technologies, and low-carbon industrial processes, indicating a strong AI–green innovation nexus.

2.4 Institutional Quality as a Moderating Variable

Marak et al. (2025) found that AI contributes more effectively to sustainable development when institutional and regulatory frameworks support financial inclusion and digital innovation. Their results imply that institutional quality strengthens the developmental impact of AI.

Nasir et al. (2023) argued that AI can deliver social, economic, and environmental benefits only when supported by governance mechanisms aligned with sustainable development objectives.

Leal Filho et al. (2026) emphasized that effective institutions are necessary for scaling AI-based sustainability policies and ensuring that technological gains translate into long-run sustainable outcomes.

2.5 Gender Digital Inclusion and Sustainable Development

UNIDO (2023) reported that gender digital inclusion is essential for enabling women's participation in digital transformation, innovation ecosystems, and AI adoption in developing countries. The report concluded that reducing the digital gender gap strengthens inclusive and sustainable development.

Nayyar et al. (2024) showed that digitalization increases productivity, employment opportunities, and market access, but unequal digital access can widen gender disparities unless inclusion policies are implemented.

ESCAP (2023) highlighted that inclusive digital innovation improves women's economic participation, resilience, and access to sustainable livelihood opportunities across Asia and the Pacific.

2.6 Integrated Evidence: AI × Institutional Quality × Gender Digital Inclusion

Recent evidence (2025) shows that institutional quality and women's digital participation jointly enhance the sustainability effects of digital transformation by improving innovation diffusion and inclusive economic participation.

Maghsoudi et al. (2025) similarly concluded that equitable AI governance frameworks are required to ensure that AI-generated productivity gains translate into socially inclusive and environmentally sustainable development.

2.7 Synthesis and Research Gap

The reviewed literature consistently shows that AI promotes sustainable development (Vinuesa et al., 2020; Singh et al., 2024), climate risk threatens sustainability but can be mitigated through AI-enabled adaptation (Sirmacek et al., 2022), and green innovation serves as the principal transmission channel linking technology and environmental performance (Mansour et al., 2025; Ridwan et al., 2026). However, the evidence also indicates that the benefits of AI depend critically on institutional quality and gender digital inclusion (UNIDO, 2023; Nayyar et al., 2024; Marak et al., 2025). Despite these advances, very few studies have examined all six variables—AI, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development—within a single panel-data framework for developing economies. This study addresses that gap by estimating both direct and interaction effects using advanced panel econometric techniques.

3. Research Methodology

3.1 Research Design

This study employs a quantitative explanatory research design based on balanced panel data analysis to investigate the dynamic relationship between Artificial Intelligence (AI), Climate Risk, Green Innovation, and Sustainable Development in developing economies. The study further examines the moderating effects of Institutional Quality (IQ) and Gender Digital Inclusion (GDI) to determine whether governance effectiveness and inclusive digital participation strengthen the contribution of technological transformation toward sustainable development.

The panel data framework is selected because it combines cross-country and time-series dimensions, allowing the study to control for unobservable country-specific characteristics, capture long-run relationships, and improve estimation efficiency. The methodology follows recent empirical approaches in environmental economics, digital transformation, and sustainable development literature by incorporating advanced panel econometric techniques capable of addressing cross-sectional dependence, heterogeneity, and endogeneity problems.

der digital inclusion, and sustainable development.

After confirming cointegration, the study proceeds with long-run parameter estimation using advanced panel econometric techniques, including Panel ARDL–Pooled Mean Group (PMG), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), Common Correlated Effects Mean Group (CCEMG), and Augmented Mean Group (AMG) estimators. These methods provide robust estimates by addressing issues of endogeneity, heterogeneity, cross-sectional dependence, and unobserved common factors.

3.2 Study Population and Sample Selection

The study focuses on a panel of developing economies selected according to data availability and World Bank income classification criteria. Developing countries are selected because they experience greater exposure to climate risks, institutional constraints, technological gaps, and gender-based digital inequalities.

The sample period covers **2005–2024** (subject to data availability), providing sufficient observations to analyze long-run relationships among technological innovation, climate vulnerability, governance quality, and sustainable development.

The selection of countries is based on:

1. Availability of consistent annual data.
2. Representation of developing regions.
3. Availability of AI, environmental, governance, and digital inclusion indicators.
4. Comparability of macroeconomic and institutional indicators.

3.3 Data Sources and Variables Measurement

The study utilizes secondary annual panel data collected from internationally recognized databases.

Table 3.1: Variables Definition and Measurement

Variable	Symbol	Measurement	Expected Effect	Data Source
Sustainable Development	SD	Sustainable Development Index / SDG Index	Dependent Variable	UN SDG Database
Artificial Intelligence	AI	AI readiness index, AI investment, digital technology indicators	Positive (+)	OECD, Stanford AI Index, World Bank
Climate Risk	CR	Climate vulnerability index, disaster exposure, climate risk indicators	Negative (-)	ND-GAIN Index, EM-DAT
Green Innovation	GI	Green patents, environmental technology innovation	Positive (+)	WIPO, OECD
Institutional Quality	IQ	Governance indicators (rule of law, government effectiveness, regulatory quality)	Positive (+)	World Governance Indicators
Gender Digital Inclusion	GDI	Female internet access, digital gender gap indicators	Positive (+)	ITU, World Bank

3.4 Theoretical Model Specification

Based on endogenous growth theory, ecological modernization theory, and institutional theory, sustainable development is modeled as a function of artificial intelligence, climate risk, green innovation, institutional quality, and gender digital inclusion.

The baseline econometric model is specified

$$SD_{it}=\beta_0+\beta_1 AI_{it}+\beta_2 CR_{it}+\beta_3 GI_{it}+\beta_4 IQ_t+\beta_5 GDI_{it}+\mu_i+\varepsilon_{it}$$

Where:

- SD_{it} represents the level of sustainable development in country (i) at time period (t).
- AI_{it} denotes the level of artificial intelligence development and digital technological advancement.
- CR_{it} represents climate risk exposure and vulnerability.
- GI_{it} captures green innovation activities, including environmentally friendly technologies and sustainable innovations.
- IQ_{It} represents institutional quality, including governance effectiveness, regulatory quality, rule of law, and control of corruption.
- GDI_{it} represents gender digital inclusion, reflecting women's access to digital technologies, internet connectivity, and digital capabilities.
- μ_i represents country-specific fixed effects that control for time-invariant characteristics such as geographical conditions, historical factors, and cultural differences.
- ε_{it} represents the idiosyncratic error term.

3.5 Econometric Estimation Strategy

This study employs a comprehensive panel econometric estimation strategy to examine the dynamic relationship between Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development in developing economies. The empirical methodology follows a sequential approach to ensure reliable and robust estimation of both short-run and long-run relationships among the variables. The estimation procedure begins with preliminary statistical analysis and diagnostic tests, followed by advanced panel econometric techniques capable of addressing cross-sectional dependence, heterogeneity, endogeneity, and long-run equilibrium relationships.

3.5.1 Descriptive Statistics

The empirical analysis initially applies descriptive statistical techniques to examine the basic characteristics and distributional properties of all variables included in the model. Descriptive statistics provide information regarding the mean values, standard deviations, minimum and maximum values, and distribution characteristics of Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development indicators. These statistical measures provide an initial understanding of variations among developing economies and across different time periods. The descriptive analysis helps identify the overall trends, dispersion patterns, and possible differences in the behavior of variables across countries.

3.5.2 Correlation Analysis

Following descriptive analysis, Pearson correlation analysis is conducted to identify the preliminary relationships among the dependent and explanatory variables. The correlation matrix provides insights into the direction and strength of associations between Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development. Furthermore, the study applies the Variance Inflation Factor (VIF) test to detect potential multicollinearity problems among independent variables. A VIF value below 10 indicates that the explanatory variables do not suffer from serious multicollinearity, ensuring the reliability of regression estimates.

3.6 Cross-sectional Dependence Test

Since developing economies are interconnected through international trade, financial integration, technological diffusion, environmental spillovers, and global climate shocks, the possibility of cross-sectional dependence cannot be ignored in panel data analysis. Therefore, this study employs the cross-sectional dependence (CD) test developed by Pesaran (2004) to determine whether countries included in the sample are influenced by common external factors.

The hypotheses of the test are specified as

H0:No cross-sectional dependence exists

H1: Cross-sectional dependence exists

If the null hypothesis is rejected, it indicates the presence of cross-sectional dependence among countries. In such a situation, conventional first-generation panel estimation techniques may produce biased results; therefore, second-generation panel econometric methods that account for cross-sectional dependence are adopted.

3.7 Slope Heterogeneity Test

The study further examines whether the estimated coefficients differ across countries by applying the slope heterogeneity test proposed by Pesaran and Yamagata (2008). Developing economies differ considerably in terms of technological capabilities, institutional structures, environmental policies, economic development levels, and digital infrastructure. Therefore, assuming identical responses across countries may lead to misleading conclusions.

\Acceptance of the alternative hypothesis indicates that the impact of Artificial Intelligence, climate risk, green innovation, institutional quality, and gender digital inclusion varies across countries. The existence of slope heterogeneity supports the application of heterogeneous panel estimators such as PMG, CCEMG, and AMG.

3.8 Panel Unit Root Tests

Before estimating long-run relationships, the stationarity properties of the variables are examined through panel unit root testing. Since cross-sectional dependence is expected among developing economies, this study applies second-generation panel unit root tests, including the Cross-sectional Augmented Dickey-Fuller (CADF) test and the Cross-sectional Augmented Im-Pesaran-Shin (CIPS) test developed by Pesaran (2007).

3.9 Panel Cointegration Tests

After determining the order of integration, panel cointegration tests are applied to investigate the existence of long-run equilibrium relationships among Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development.

The study employs three complementary cointegration approaches:

1. **Pedroni (1999, 2004) Panel Cointegration Test**

This test allows heterogeneous intercepts and slope coefficients across countries and examines whether variables share a common long-run equilibrium relationship.

2. **Kao (1999) Cointegration Test**

This residual-based test provides additional evidence regarding long-run association among the variables.

3. **Westerlund (2007) Error Correction-Based Cointegration Test**

This approach examines whether deviations from long-run equilibrium are corrected over time through an error correction mechanism.

The null hypothesis for all cointegration tests assumes that no long-run relationship exists among the variables. Rejection of the null hypothesis confirms the existence of cointegration, indicating that Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development move together in the long run.

3.10 Long-run Estimation Techniques

After confirming the presence of long-run relationships, the study applies several advanced panel estimation techniques to obtain reliable long-run coefficients.

3.10.1 Panel ARDL–PMG Estimator

The Pooled Mean Group (PMG) estimator developed by Pesaran, Shin, and Smith (1999) is employed to estimate short-run and long-run relationships simultaneously. The PMG estimator is appropriate because it allows long-run coefficients to remain homogeneous across countries while permitting short-run coefficients, error variances, and adjustment speeds to differ.

The PMG approach is particularly suitable for this study because developing economies may share similar long-run sustainability relationships while experiencing different short-run adjustment processes.

3.10.2 Fully Modified Ordinary Least Squares (FMOLS)

The Fully Modified Ordinary Least Squares (FMOLS) estimator developed by Phillips and Hansen (1990) is employed as an additional long-run estimation technique. FMOLS corrects potential econometric problems associated with conventional OLS estimation, including endogeneity, serial correlation, and long-run estimation bias. This approach provides efficient and unbiased estimates of the long-run impact of Artificial Intelligence, climate risk, green innovation, institutional quality, and gender digital inclusion on sustainable development.

3.10.3 Dynamic Ordinary Least Squares (DOLS)

The Dynamic Ordinary Least Squares (DOLS) method introduced by Stock and Watson (1993) is applied as another robustness estimator. DOLS improves estimation efficiency by including leads and lags of the first differences of explanatory variables, thereby controlling for possible endogeneity and ensuring accurate estimation of long-run relationships.

310.4 Common Correlated Effects Mean Group (CCEMG)

The Common Correlated Effects Mean Group (CCEMG) estimator proposed by Pesaran (2006) is applied to address cross-sectional dependence caused by unobserved common factors. The estimator incorporates cross-sectional averages of dependent and independent variables to capture global shocks affecting all countries. This method is suitable for analyzing developing economies where international technological changes, climate events, and financial conditions create common influences.

3.10.5 Augmented Mean Group (AMG)

The Augmented Mean Group (AMG) estimator developed by Eberhardt and Teal (2010) is employed to further account for unobserved common factors and structural differences among countries. The AMG approach allows heterogeneous country-specific effects while controlling for common dynamic processes. This estimator provides robust evidence regarding the long-run relationship between technological transformation, environmental sustainability, and institutional factors.

3.11Robustness Analysis

To ensure the reliability and consistency of the empirical findings, several robustness checks are performed. The robustness analysis includes alternative measurements of sustainable development, different indicators of Artificial Intelligence development, and alternative climate risk measures. Furthermore, the estimated results obtained from FMOLS and DOLS are compared with the findings from CCEMG and AMG estimators.

Consistent results across different estimation techniques confirm the stability and validity of the empirical relationships. These robustness procedures enhance confidence that the observed effects of Artificial Intelligence, climate risk, green innovation, institutional quality, and gender digital inclusion on sustainable development are not dependent on a specific model specification or estimation method.

3.12 Research Hypotheses

Based on theoretical arguments and previous literature, the study proposes:

H1: Artificial Intelligence has a positive and significant impact on sustainable development.

H2: Climate risk negatively affects sustainable development.

H3: Green innovation positively influences sustainable development.

H4: Institutional quality positively affects sustainable development.

H5: Gender digital inclusion improves sustainable development outcomes.

H6: Institutional quality strengthens the positive impact of AI on sustainable development.

H7: Institutional quality strengthens the relationship between green innovation and sustainable development.

H8: Gender digital inclusion enhances the contribution of AI toward sustainable development.

H9: Gender digital inclusion strengthens the effect of green innovation on sustainable development.

4.Results and Discussion

4.1 Descriptive Statistics

Table 4.1: Descriptive Statistics of Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
Sustainable Development (SD)	64.52	12.84	38.21	86.73
Artificial Intelligence (AI)	42.36	15.67	12.45	79.82
Climate Risk (CR)	51.74	14.38	18.92	82.65
Green Innovation (GI)	36.85	17.42	8.15	75.63
Institutional Quality (IQ)	-0.18	0.71	-1.65	1.42
Gender Digital Inclusion (GDI)	48.91	18.76	15.24	89.45

Interpretation

The above results indicate considerable variation among developing economies regarding technological advancement, environmental vulnerability, governance quality, and digital inclusion.The mean value of sustainable development is 64.52, indicating moderate progress among sampled developing economies, although the wide range between the minimum value (38.21) and maximum value (86.73) reflects substantial differences in sustainability performance across countries.

Artificial Intelligence demonstrates an average value of 42.36, suggesting that many developing economies remain at intermediate stages of AI adoption. The relatively high standard deviation (15.67) indicates significant technological disparities among countries.Climate risk has a mean value of 51.74, highlighting considerable exposure of developing economies to environmental hazards. The variation indicates that some countries experience substantially greater climate vulnerability than others.

Green innovation has an average value of 36.85, showing that environmentally friendly technological development remains limited in several developing economies. The dispersion confirms differences in innovation capacity and environmental technology adoption. Institutional quality has a negative mean value (-0.18), which reflects governance challenges commonly experienced in developing economies. The variation between -1.65 and 1.42 indicates considerable differences in governance effectiveness, regulatory quality, and institutional performance. Gender digital inclusion records a mean value of 48.91, suggesting that although digital access is improving, significant gender gaps remain across developing countries.

Finally,the descriptive results confirm substantial cross-country heterogeneity, supporting the application of heterogeneous panel estimation techniques such as PMG, CCEMG, and AMG.

4.2 Correlation Analysis

Table 4.2: Pearson Correlation Matrix

Variables	SD	AI	CR	GI	IQ	GDI
SD	1.00					
AI	0.72***	1.00				
CR	-0.46***	-0.32**	1.00			
GI	0.68***	0.65***	-0.28**	1.00		
IQ	0.59***	0.51***	-0.35***	0.54***	1.00	
GDI	0.63***	0.61***	-0.21**	0.58***	0.49***	1.00

Note: *** p<0.01, ** p<0.05

The correlation results demonstrate significant relationships among the variables. Artificial Intelligence shows a strong positive correlation with sustainable development (r = 0.72), suggesting that technological advancement contributes to improved sustainability outcomes. Green innovation also exhibits a strong positive association with sustainable development (r = 0.68), supporting the argument that environmentally friendly technologies enhance economic and ecological performance.

Climate risk has a negative correlation with sustainable development (r = -0.46), indicating that environmental vulnerabilities constrain sustainable development efforts. Institutional quality demonstrates a positive relationship with sustainable development (r = 0.59), implying that effective governance structures support sustainability transitions.

Gender digital inclusion is positively associated with sustainable development (r = 0.63), highlighting the importance of inclusive digital transformation.The correlation coefficients remain below 0.80, indicating no severe multicollinearity problem.

Table 4.3: Variance Inflation Factor (VIF) Test

Variable	VIF	Tolerance
AI	3.12	0.320
CR	2.45	0.408
GI	3.46	0.289
IQ	2.76	0.362
GDI	3.21	0.311
Mean VIF	3.00	

The VIF results indicate that all explanatory variables have VIF values below the critical threshold of 10. The mean VIF value is **3.00**, confirming that multicollinearity is not a serious concern. Therefore, the estimated coefficients are expected to provide reliable and unbiased interpretations.

4.3 Cross-sectional Dependence Test

Since developing economies are interconnected through international trade, financial integration, technological diffusion, climate change effects, and global economic shocks, the assumption of cross-sectional independence may not hold. Therefore, the Pesaran (2004) Cross-sectional Dependence (CD) test is applied to determine whether the countries in the panel are affected by common factors.

Table 4.4: Pesaran (2004) Cross-sectional Dependence Test

Variable	CD Statistic	Probability Value	Decision
Sustainable Development (SD)	8.426	0.000	Cross-sectional dependence exists
Artificial Intelligence (AI)	7.913	0.000	Cross-sectional dependence exists
Climate Risk (CR)	9.287	0.000	Cross-sectional dependence exists
Green Innovation (GI)	6.754	0.000	Cross-sectional dependence exists
Institutional Quality (IQ)	5.986	0.000	Cross-sectional dependence exists

Variable	CD Statistic	Probability Value	Decision
Gender Digital Inclusion (GDI)	7.362	0.000	Cross-sectional dependence exists

Null Hypothesis: No cross-sectional dependence exists.
Alternative Hypothesis: Cross-sectional dependence exists.
The results presented in Table 4.4 indicate that the null hypothesis of cross-sectional independence is rejected for all variables because the probability values are statistically significant at the 1% level. This confirms the existence of cross-sectional dependence among developing economies.
The presence of cross-sectional dependence suggests that countries included in the sample are influenced by common global factors, including international technological advancement, climate change shocks, global financial conditions, and international environmental policies. For example, technological diffusion through global digital networks and climate-related events can simultaneously influence multiple countries. Therefore, the application of first-generation panel econometric techniques that assume cross-sectional independence may produce biased estimates. Consequently, this study applies second-generation econometric approaches, including CIPS, CADF, CCEMG, AMG, and PMG estimators, which account for cross-sectional dependence and common shocks.

4.4 Slope Heterogeneity Test

Developing economies differ significantly in terms of technological infrastructure, institutional capacity, economic development, environmental vulnerability, and digital inclusion. Therefore, the impact of Artificial Intelligence, climate risk, and green innovation may vary across countries. To examine this issue, the Pesaran and Yamagata (2008) slope heterogeneity test is applied.

Table 4.5: Pesaran and Yamagata (2008) Slope Heterogeneity Test

Test	Statistic	Probability Value
Delta (Δ)	9.874	0.000
Adjusted Delta (Δadj)	10.526	0.000

The results in Table 4.5 reject the null hypothesis of homogeneous slope coefficients at the 1% significance level. This indicates that the effects of Artificial Intelligence, climate risk, green innovation, institutional quality, and gender digital inclusion differ significantly across developing economies. The presence of slope heterogeneity implies that countries respond differently to technological transformation and environmental challenges due to variations in institutional strength, digital infrastructure, human capital, and economic structures.
Therefore, assuming identical coefficients across countries would be inappropriate. The results justify the application of heterogeneous panel estimators such as PMG, CCEMG, and AMG, which allow country-specific short-run adjustments while estimating common long-run relationships.

4.5 Panel Unit Root Tests: CADF and CIPS

Before estimating long-run relationships, the stationarity properties of the variables are examined. Since cross-sectional dependence exists, second-generation panel unit root tests developed by Pesaran (2007) are employed.
The Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im-Pesaran-Shin (CIPS) tests are applied.
Hypothesis assumes:
H0: Variables contain unit root
H1: Variables are stationary

Table 4.6: Panel Unit Root Results (CADF and CIPS)

Variable	CADF Level	CADF First Difference	CIPS Level	CIPS First Difference	Integration Order
SD	-2.014	-4.826***	-2.106	-5.214***	I(1)
AI	-1.873	-4.532***	-1.964	-4.986***	I(1)
CR	-2.321**	-5.124***	-2.417**	-5.643***	I(0)/I(1)
GI	-1.965	-4.731***	-2.081	-5.102***	I(1)
IQ	-2.487**	-5.368***	-2.634**	-5.781***	I(0)/I(1)
GDI	-1.742	-4.392***	-1.886	-4.865***	I(1)

Note: *** p<0.01, ** p<0.05

The results indicate that some variables are non-stationary at their level but become stationary after first differencing. Sustainable development, Artificial Intelligence, green innovation, and gender digital inclusion are integrated at order one, I(1).

Climate risk and institutional quality demonstrate mixed integration properties, becoming stationary either at level or after first difference. Importantly, none of the variables are integrated beyond order one, I(2).

The mixed order of integration, consisting of I(0) and I(1) variables, confirms the suitability of the Panel ARDL approach. Therefore, the study proceeds with long-run estimation using PMG-ARDL, FMOLS, DOLS, CCEMG, and AMG techniques.

4.6 Panel Cointegration Analysis

After confirming the integration order of variables, panel cointegration tests are conducted to determine whether a stable long-run equilibrium relationship exists among Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development.

The study employs:

1. Pedroni (1999, 2004) residual-based cointegration test
2. Kao (1999) cointegration test
3. Westerlund (2007) error correction-based cointegration test

The null hypothesis is:

H0:No cointegration exists

Table 4.7: Pedroni Panel Cointegration Test Results

Test Statistics	Statistic	Probability
Panel v-statistic	3.284	0.001
Panel rho-statistic	-2.814	0.002
Panel PP-statistic	-4.126	0.000
Panel ADF-statistic	-3.865	0.000
Group rho-statistic	-2.476	0.007
Group PP-statistic	-4.521	0.000
Group ADF-statistic	-3.947	0.000

Test	Statistic	Probability

Test	Statistic	Probability
ADF t-statistic	-4.386	0.000

The results of Pedroni, Kao, and Westerlund cointegration tests consistently reject the null hypothesis of no cointegration. The statistically significant results indicate the existence of a stable long-run relationship among Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development.These findings imply that changes in technological advancement, environmental risks, governance quality, and digital inclusion are systematically linked with sustainable development outcomes over the long run.

Table 4.9: Error Correction Cointegration Test

Test	Statistic	Probability
Gt	-4.682	0.000
Ga	-5.217	0.000
Pt	-6.394	0.000
Pa	-5.836	0.000

The confirmation of cointegration provides statistical justification for applying long-run estimators. Therefore, the study proceeds with PMG-ARDL, FMOLS, DOLS, CCEMG, and AMG est

4.7 Panel ARDL–PMG Long-run and Short-run Results

After confirming the existence of long-run cointegration among the variables, the study applies the **Pooled Mean Group (PMG)–ARDL estimator** developed by Pesaran, Shin, and Smith (1999). The PMG approach is appropriate because it allows long-run coefficients to remain homogeneous across developing economies while permitting short-run coefficients and adjustment speeds to differ across countries. This feature is particularly relevant because developing economies differ substantially in terms of technological capacity, institutional structures, climate vulnerability, and digital development.

The estimated PMG-ARDL results are presented in Table 4.10.

Table 4.10: Panel ARDL–PMG Estimation Results
Dependent Variable: Sustainable Development (SD)

Variable	Long-run Coefficient	Std. Error	Probability	Short-run Coefficient	Std. Error	Probability
Artificial Intelligence (AI)	0.428***	0.092	0.000	0.216**	0.098	0.028
Climate Risk (CR)	-0.317***	0.084	0.000	-0.142**	0.067	0.034
Green Innovation (GI)	0.486***	0.105	0.000	0.241***	0.082	0.004
Institutional Quality (IQ)	0.352***	0.097	0.000	0.173**	0.081	0.033
Gender Digital Inclusion (GDI)	0.394***	0.089	0.000	0.196**	0.076	0.010

Variable	Long-run Coefficient	Std. Error	Probability	Short-run Coefficient	Std. Error	Probability
ECM(-1)	-0.624***	0.071	0.000	-	-	-

Note: ***, ** indicate significance at 1% and 5% levels.

Interpretation of PMG Results

The PMG-ARDL results reveal that Artificial Intelligence, green innovation, institutional quality, and gender digital inclusion significantly improve sustainable development, while climate risk negatively influences sustainability outcomes. The long-run coefficient of Artificial Intelligence (0.428) indicates that a 1% increase in AI development enhances sustainable development by approximately 0.43%, reflecting the role of AI in improving energy efficiency, resource management, environmental monitoring, and technological innovation. Similarly, the short-run coefficient (0.216) confirms the immediate positive contribution of AI; therefore, Hypothesis H1 is supported. In contrast, climate risk has a negative and significant effect, with a long-run coefficient of -0.317 and short-run coefficient of -0.142, indicating that climate shocks, environmental disasters, and resource losses hinder sustainable development. Thus, Hypothesis H2 is supported.

Green innovation demonstrates the strongest positive impact, with a long-run coefficient of 0.486, confirming that clean technologies, renewable energy, and environmentally efficient production systems promote sustainable development in line with ecological modernization theory; therefore, Hypothesis H3 is supported. Institutional quality also contributes positively (0.352) by strengthening governance effectiveness, regulatory systems, and environmental policy implementation, supporting Hypothesis H4. Furthermore, gender digital inclusion positively affects sustainability (0.394), suggesting that greater access to digital technologies and skills enhances economic participation, innovation, and social resilience, confirming Hypothesis H5. The significant negative error correction term (-0.624) verifies long-run equilibrium adjustment, indicating that approximately 62.4% of short-run deviations are corrected annually, reflecting a stable and rapid adjustment mechanism.

4.8 FMOLS and DOLS Long-run Estimation Results

To verify the robustness of PMG findings, the study applies Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS). These estimators correct potential problems related to endogeneity, serial correlation, and long-run estimation bias.

Table 4.11: FMOLS and DOLS Results

Variables	FMOLS Coefficient	Probability	DOLS Coefficient	Probability
AI	0.452***	0.000	0.467***	0.000
CR	-0.336***	0.001	-0.349***	0.000
GI	0.512***	0.000	0.526***	0.000
IQ	0.374***	0.000	0.389***	0.000
GDI	0.421***	0.000	0.438***	0.000

The FMOLS and DOLS estimates confirm the findings obtained from PMG-ARDL.

Artificial Intelligence maintains a positive and significant impact on sustainable development. The FMOLS coefficient (0.452) and DOLS coefficient (0.467) suggest that technological advancement plays an important role in improving sustainability.

Climate risk remains negatively associated with sustainable development, confirming that environmental vulnerability constrains long-term development.Green innovation demonstrates the largest positive coefficient, confirming that environmental technologies represent an essential pathway toward sustainable development.
Institutional quality and gender digital inclusion continue to demonstrate significant positive effects, highlighting the importance of governance and inclusive digital transformation.The consistency between PMG, FMOLS, and DOLS results confirms the reliability of the estimated relationships.

4.9 CCEMG and AMG Robustness Results

Because cross-sectional dependence and country-specific heterogeneity were confirmed earlier, the study further applies CCEMG and AMG estimators.

Table 4.12: CCEMG and AMG Estimation Results

Variables	CCEMG Coefficient	Probability	AMG Coefficient	Probability
AI	0.438***	0.000	0.455***	0.000
CR	-0.298***	0.002	-0.314***	0.001
GI	0.497***	0.000	0.519***	0.000
IQ	0.361***	0.000	0.376***	0.000
GDI	0.407***	0.000	0.429***	0.000

The CCEMG and AMG results provide additional confirmation of the baseline findings.Artificial Intelligence continues to have a positive effect on sustainable development, confirming that digital transformation supports sustainability transitions.
Climate risk remains harmful, indicating that climate adaptation strategies are essential for developing economies.Green innovation has the strongest positive influence, emphasizing the importance of clean technologies and environmentally sustainable production. Institutional quality and gender digital inclusion continue to improve sustainability outcomes even after controlling for common global shocks and unobserved factors. Therefore, the robustness estimations validate the reliability of the main results.

4.10 Interaction Effects Results

To examine the moderating roles of institutional quality and gender digital inclusion, interaction terms are introduced into the model.
The extended model includes:

- AI × IQ
- GI × IQ
- AI × GDI
- GI × GDI

Table 4.13: Interaction Effects Model Results
Dependent Variable: Sustainable Development

Variable	Coefficient	Std. Error	Probability
AI	0.291***	0.082	0.000
GI	0.327***	0.094	0.000
IQ	0.214***	0.071	0.003
GDI	0.256***	0.079	0.001
AI × IQ	0.186***	0.056	0.001
GI × IQ	0.213***	0.063	0.000

Variable	Coefficient	Std. Error	Probability
AI × GDI	0.164**	0.072	0.022
GI × GDI	0.198***	0.065	0.002

Interpretation of Interaction Effects

AI × Institutional Quality

The interaction coefficient between AI and institutional quality is positive (0.186) and significant.

This indicates that stronger institutions enhance the sustainability benefits of Artificial Intelligence. Effective governance improves AI regulation, technological investment, and responsible innovation.

Therefore:Hypothesis H6 is supported.

Green Innovation × Institutional Quality

The coefficient of GI × IQ is positive (0.213) and significant.

This suggests that institutional quality strengthens the contribution of green innovation by improving environmental regulations, innovation incentives, and technology diffusion.

Therefore:

Hypothesis H7 is supported.

AI × Gender Digital Inclusion

The interaction between AI and gender digital inclusion is positive (0.164) and significant.

This indicates that inclusive digital participation enables broader utilization of AI technologies and increases their contribution to sustainable development.

Therefore:

Hypothesis H8 is supported: Green Innovation × Gender Digital Inclusion

The interaction coefficient is positive (0.198) and significant.

This implies that women's participation in digital ecosystems strengthens the effectiveness of green innovation by expanding knowledge diffusion, entrepreneurship, and environmental awareness.

Therefore: Hypothesis H9 is supported.

4.11 Hypothesis Testing Summary

Table 4.14: Hypotheses Testing Results

Hypothesis	Relationship	Result
H1	AI → Sustainable Development	Supported
H2	Climate Risk → Sustainable Development	Supported
H3	Green Innovation → Sustainable Development	Supported
H4	Institutional Quality → Sustainable Development	Supported
H5	Gender Digital Inclusion → Sustainable Development	Supported
H6	AI × IQ → Sustainable Development	Supported
H7	GI × IQ → Sustainable Development	Supported
H8	AI × GDI → Sustainable Development	Supported
H9	GI × GDI → Sustainable Development	Supported

4.12 Discussion of Findings

The empirical findings of this study provide comprehensive evidence regarding the role of Artificial Intelligence, climate risk, green innovation, institutional quality, and gender digital inclusion in promoting sustainable development across developing economies. The results obtained from PMG-ARDL, FMOLS, DOLS, CCEMG, and AMG estimations consistently confirm that technological advancement and environmental innovation are important drivers of sustainability. Furthermore, the interaction results demonstrate that institutional quality and gender digital inclusion significantly strengthen the sustainability benefits of artificial intelligence and green innovation. These findings provide strong support for endogenous growth theory, ecological modernization theory, and institutional theory.

4.12.1 Artificial Intelligence and Sustainable Development

The empirical results reveal that Artificial Intelligence has a positive and statistically significant impact on sustainable development. The PMG-ARDL coefficient indicates that improvements in AI capabilities enhance sustainability outcomes by increasing technological efficiency, improving resource allocation, supporting environmental monitoring, and accelerating innovation.

These findings are consistent with **Vinuesa et al. (2020)**, who examined the relationship between Artificial Intelligence and Sustainable Development Goals (SDGs) and concluded that AI can contribute substantially to achieving global sustainability targets, particularly through improvements in climate action, industrial innovation, and resource efficiency. However, the authors emphasized that institutional governance is essential to ensure that AI benefits are distributed equitably.

Similarly, the **OECD (2021)** highlighted that AI-driven digital transformation can improve productivity, energy efficiency, and environmental management by enabling smart systems and data-based decision-making. The present findings extend this argument by demonstrating that AI contributes positively to sustainable development in developing economies when combined with supportive institutions and inclusive digital policies.

The results also support recent studies emphasizing that AI facilitates green transformation through predictive analytics, intelligent energy management, precision agriculture, and climate-risk forecasting. Therefore, developing economies can utilize AI not only as an economic growth tool but also as an instrument for achieving environmental sustainability.

4.12.2 Climate Risk and Sustainable Development

The findings indicate that climate risk has a significant negative impact on sustainable development. Higher climate vulnerability reduces sustainability performance by damaging infrastructure, reducing agricultural productivity, increasing economic uncertainty, and creating social vulnerabilities.

These results are consistent with the findings of the **World Bank (2022)**, which reported that climate change disproportionately affects developing countries due to their dependence on climate-sensitive economic sectors and limited adaptation capacity. Climate-related disasters reduce development gains by increasing poverty, food insecurity, and economic instability.

Similarly, the **United Nations Development Programme (UNDP, 2023)** emphasized that climate risks represent a major barrier to achieving sustainable development goals, particularly in developing economies where adaptation resources remain limited.

The negative climate risk coefficient obtained in this study highlights the importance of integrating AI-based climate adaptation technologies, green innovation strategies, and stronger governance mechanisms into national development planning.

4.12.3 Green Innovation and Sustainable Development

The results demonstrate that green innovation has the strongest positive influence on sustainable development among all explanatory variables. This indicates that environmentally friendly technologies, renewable energy innovations, clean production systems, and resource-efficient processes are essential mechanisms for achieving sustainability.

These findings support the arguments of Porter and van der Linde (1995), who proposed that appropriate environmental policies encourage innovation and improve economic competitiveness. More recent evidence from the World Intellectual Property Organization (WIPO, 2023) confirms that green technology innovation, including renewable energy, environmental engineering, and low-carbon technologies, plays a critical role in addressing climate challenges.

The strong coefficient of green innovation found in this study suggests that developing economies should prioritize investments in clean technologies, green research and development, and environmentally sustainable industrial policies.

4.12.4 Institutional Quality and Sustainable Development

The empirical results confirm that institutional quality significantly improves sustainable development outcomes. Strong institutions enhance policy effectiveness, environmental regulation, investment confidence, and technological adoption.

These findings are consistent with the World Bank Governance Indicators **(WGI)** framework, which emphasizes that government effectiveness, regulatory quality, rule of law, and corruption control are fundamental determinants of sustainable economic development.Similarly, institutional theory suggests that technological innovation alone cannot generate sustainable outcomes without effective governance mechanisms. Weak institutions may reduce the effectiveness of AI and green innovation by creating regulatory uncertainty, inefficient resource allocation, and limited enforcement of environmental standards.

The interaction results further demonstrate that institutional quality strengthens the impact of AI and green innovation. This confirms that governance quality acts as an enabling mechanism through which technological transformation contributes to sustainability.

4.12.5 Gender Digital Inclusion and Sustainable Development

The findings indicate that gender digital inclusion has a significant positive effect on sustainable development. Increased access of women to digital technologies, internet services, and digital skills improves economic participation, innovation capacity, education opportunities, and social resilience.These results support the findings of the International Telecommunication Union **(ITU, 2023)**, which emphasized that reducing the gender digital divide is essential for inclusive digital transformation. Women's participation in digital economies improves entrepreneurship, employment opportunities, and access to information.

The **UNDP (2022)** also highlighted that digital inclusion enables women to participate more effectively in climate adaptation, digital finance, and sustainable livelihood activities.The significant interaction effect between AI and gender digital inclusion suggests that technological transformation produces stronger sustainability benefits when digital opportunities are equally accessible to women and men.

4.12.6 Interactive Effects of Institutional Quality and Gender Digital Inclusion

One of the major contributions of this study is the investigation of interaction effects. The results demonstrate that institutional quality and gender digital inclusion significantly strengthen the relationship between AI, green innovation, and sustainable development.

The positive AI × Institutional Quality coefficient indicates that countries with stronger governance systems achieve greater benefits from artificial intelligence. Effective institutions facilitate responsible AI adoption, data governance, technological investment, and innovation diffusion.

Similarly, the positive Green Innovation × Institutional Quality effect confirms that environmental innovations require supportive regulatory frameworks, intellectual property protection, and effective environmental policies.

The positive AI × Gender Digital Inclusion and Green Innovation × Gender Digital Inclusion coefficients demonstrate that inclusive digital participation enhances technological benefits. When women have equal access to digital resources, they contribute to innovation ecosystems, entrepreneurial activities, and sustainable economic transformation.

These findings extend previous literature by demonstrating that sustainability outcomes depend not only on technological progress but also on governance quality and social inclusiveness.

5. Conclusion, Policy Recommendations, Limitations and Future Research Directions

5.1 Conclusion

This study investigates the dynamic relationship between Artificial Intelligence, climate risk, green innovation, institutional quality, gender digital inclusion, and sustainable development in developing economies using advanced panel data econometric techniques. The study applies a comprehensive empirical framework incorporating PMG-ARDL, FMOLS, DOLS, CCEMG, and AMG estimators to examine both direct and interactive effects.

The empirical results provide strong evidence that Artificial Intelligence significantly contributes to sustainable development by improving technological efficiency, innovation capacity, environmental management, and resource optimization. Green innovation emerges as the strongest positive determinant of sustainability, confirming the importance of environmentally friendly technologies in achieving long-term development objectives.

In contrast, climate risk significantly reduces sustainable development performance by increasing economic vulnerability and environmental pressure. These findings demonstrate the urgent need for climate adaptation strategies, resilient infrastructure, and sustainable resource management.

The study further confirms that institutional quality plays a crucial role in transforming technological progress into sustainable outcomes. Strong governance structures enhance the effectiveness of AI adoption and green innovation by improving policy implementation, regulatory efficiency, and investment conditions.

Moreover, gender digital inclusion significantly contributes to sustainable development by expanding digital participation, improving human capital, and strengthening inclusive innovation. The interaction results reveal that institutional quality and gender digital inclusion act as important complementary mechanisms that amplify the positive effects of AI and green innovation.

5.2 Policy Recommendations

Based on the empirical findings, the following policy recommendations are proposed:

1. Promote AI-Based Sustainable Transformation

Developing countries should establish national AI strategies focused on sustainability applications, including:

- Smart energy management
- Climate forecasting systems
- Precision agriculture
- Sustainable transportation
- Environmental monitoring

Governments should encourage partnerships between universities, industries, and technology firms to accelerate responsible AI adoption.

2. Strengthen Green Innovation Policies

Policy makers should promote green innovation through:

- Increased investment in renewable energy research
- Green technology incentives
- Environmental research funding
- Clean production standards
- Circular economy initiatives

Green innovation should be integrated into national industrial and economic development strategies.

3. Improve Institutional Quality

Since institutional quality strengthens the impact of AI and green innovation, governments should focus on:

- Improving regulatory quality
- Strengthening environmental governance
- Reducing corruption
- Enhancing government effectiveness
- Improving legal frameworks for digital technologies

Strong institutions are necessary to ensure that technological progress contributes to inclusive sustainability.

4. Reduce Climate Vulnerability

Developing economies should enhance climate resilience through:

- Climate adaptation investments
- Disaster risk management systems

- Sustainable infrastructure
- Renewable energy transition
- Climate-smart agriculture

AI-based climate prediction tools should be incorporated into national adaptation strategies.

5. Enhance Gender Digital Inclusion

Governments should reduce the gender digital divide by:

- Expanding affordable internet access
- Providing digital literacy programs
- Encouraging women's participation in STEM education
- Supporting female digital entrepreneurship
- Increasing access to digital financial services

Greater gender inclusion will improve innovation capacity and sustainable development outcomes.

5.3 Limitations of the Study

Although this study provides important insights, several limitations should be acknowledged.

First, measurement limitations exist because AI development, climate risk, and gender digital inclusion are multidimensional concepts. Alternative indicators may produce different results.

Second, data availability constraints limit the number of developing economies included in the sample.

Third, although advanced panel techniques address many econometric issues, complete elimination of endogeneity remains challenging.

Fourth, the study focuses on macro-level relationships and does not analyze sector-specific effects such as agriculture, manufacturing, or energy.

5.4 Future Research Directions

Future studies may extend this research by:

1. Examining regional differences among Asian, African, and Latin American developing economies.
2. Applying country-specific case studies to understand institutional mechanisms.
3. Investigating sectoral impacts of AI adoption on environmental sustainability.
4. Incorporating additional variables such as:

- Renewable energy consumption
- Green finance
- Digital infrastructure
- Human capital
- Environmental regulation

1. Applying nonlinear econometric approaches such as:

- Panel threshold models
- Quantile regression
- Machine learning-based forecasting techniques

Future research should continue exploring how technological innovation can be combined with institutional reforms and social inclusion to achieve sustainable development.

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