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The Digital-Green Twin Transition: A Framework for Digital Transformation and Clean Energy Integration in the Agro-Industrial Sectors of Russia and Kazakhstan

Elvira Rustenova[1*], Aizhan Ibyzhanova[1], Aizhamal Aidaraliyeva[1], Sergey Barykin[2], Olga Voronova[2], Inessa Vyacheslavovna Penkova[3], Sara Daniali[4]

[1]Institute of Economics, IT and Vocational Training, West Kazakhstan Agrarian and Technical University named after Zhangir Khan, Uralsk, Kazakhstan, [2]Graduate School of Service and Trade, Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia, [3]Department of Economics Theory, Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia, [4]Institute of Industrial Management, Economics and Trade, Peter the Great St. Petersburg Polytechnic University, Polytechnicheskaya, St. Petersburg, Russia. *Email: elvirarustenova@gmail.com

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ABSTRACT

This study examines the relationship between Digital Transformation (DT) and Clean Energy Integration (CEI) in the agro-industrial sectors of emerging economies, with a focus on Kazakhstan and Russia. As these countries pursue industrial growth while meeting climate commitments, the research evaluates how digital maturity and green financial frameworks drive decarbonization. Using secondary data from 2000 to 2024, the study applies advanced econometric methods, including Cross-Sectionally Augmented IPS (CIPS) unit root tests and the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, to address cross-sectional dependence and structural breaks. Results show that both Digital Transformation and Environmental Policy (EP) significantly reduce Greenhouse Gas Emissions (GHGE) in the long term, with coefficients of −1.730 and −2.289, respectively. Green Financial Innovation (GFI) and Circular Capacity (CC) also play key roles in lowering carbon intensity. The Error Correction Term (ECT) of −1.120 suggests a rapid adjustment toward the long-run equilibrium. This research introduces a holistic "Digital-Green Twin" approach, positioning digitalization as the foundation for renewable energy adoption in large-scale agro-industrial processing. The findings offer a scalable roadmap for policymakers to align technological progress with carbon-neutral industrial objectives.

Keywords: Digital Transformation, Clean Energy Integration, Agro-Industrial Sector, CS-ARDL, Kazakhstan, Russia, Carbon Neutrality
JEL Classifications: Q16, O33, Q54, C23

1. INTRODUCTION

The global agro-industrial sector is undergoing a critical transformation, in which the integration of digital technologies and clean energy systems is essential to achieving long-term sustainability. In emerging economies, particularly in the Eurasian region such as Kazakhstan and Russia, the transition to "Agriculture 4.0" signifies a fundamental shift in resource management driven by environmental imperatives. Digitalization is reshaping economic structures and governance models worldwide. In leading emerging markets such as China, the widespread adoption of these technologies has initiated a "second modernization" phase, positioning the country as a technological leader and creating new opportunities for industrial growth (Qudrat-Ullah and Nevo, 2021). However, the rapid expansion of digital infrastructure also introduces significant environmental challenges, including increased energy consumption and the management of electronic waste, necessitating policies that

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balance technological progress with ecological sustainability (Khalid and Peng, 2021).

This research addresses the complex challenge of balancing energy efficiency, economic growth, and environmental protection, commonly referred to as the "trilemma" (Xia et al., 2020). Agro-industrial enterprises in emerging economies make substantial contributions to national GDP, yet often face inefficiencies in resource utilization. The global shift toward sustainable development underscores the importance of robust internal controls and both exploratory and exploitative innovation for enterprise longevity (Liu et al., 2022). Furthermore, there is increasing emphasis on green economic quality, accompanied by ongoing debates about the allocation of financing between environmental protection and social objectives (Nguyen and Khominich, 2023). Transitioning from linear resource consumption to circular economy models that emphasize recycling and waste reduction is therefore essential for achieving global sustainability targets (Schroeder et al., 2019).

Despite these developments, a significant challenge persists: agro-industrial firms in emerging markets often lack the digital maturity required to effectively integrate renewable energy sources. This shortfall leads to higher carbon emissions and increased operational costs, particularly in regions where energy consumption is closely tied to economic performance (Yang et al., 2021). Additionally, inadequate digital leadership hinders the development of a digital culture necessary for employees to manage advanced energy systems (Shin et al., 2023). Without a comprehensive framework that aligns digital capabilities with clean energy adoption, the agro-industrial sector remains vulnerable to fluctuations in global energy prices and environmental instability (Mohsin and Jamaani, 2023).

This study addresses a research gap by providing an empirical framework to examine the intersection of Industry 4.0 technologies and decentralized energy systems in the agro-industrial sectors of Kazakhstan and Russia. While existing literature recognizes the broad impact of Industry 4.0 on environmental sustainability (Ol'ah et al., 2020), few studies investigate the mediating role of a firm's IT capability between digital strategy and operational efficiency in energy-intensive agricultural processing (Wang et al., 2020). There is a critical need to explore how digital transformation can strengthen organizational resilience in these specific contexts (Zhang et al., 2021).

The objectives of this research are to: analyze the impact of digital transformation on organizational resilience and sustainable performance in agro-industrial businesses (Zhang et al., 2021); assess how green financial innovation and intellectual capital facilitate the adoption of renewable energy technologies (Ullah et al., 2022); investigate the role of sustainable management policies in improving the performance of sectors pursuing carbon neutrality (Liu et al., 2024); and develop a strategic roadmap for the agro-industrial sector that aligns corporate social responsibility with firm performance and global climate targets (Makhdoom et al., 2023; Rosati and Faria, 2019).

This research focuses on large-scale agro-industrial enterprises in Russia and Kazakhstan, analyzed from a global perspective to ensure data comparability. It introduces an integrated perspective on the "Digital-Green Twin Transition." The study contends that big data and social media analytics are fundamental to business sustainability within a participatory web environment, rather than serving solely as communication tools (Sivarajah et al., 2019). By linking environmental corporate social responsibility with partnership restructuring and firm performance, the research provides a distinctive roadmap for emerging economies to modernize their primary sectors while addressing energy poverty and resource security (Makhdoom et al., 2023; Mohsin et al., 2022).

The structure of this study is as follows: Section 1 introduces the research and outlines its objectives. Section 2 reviews the literature on digital maturity and energy transitions. Section 3 describes the methodology, focusing on the relationship between organizational learning and sustainable performance (Zgrzywa-Ziemak and Walecka-Jankowska, 2021). Section 4 presents the empirical analysis of agro-industrial energy data. Section 5 discusses the findings in relation to global sustainability benchmarks. Section 6 concludes with policy recommendations and directions for future research.

2. LITERATURE REVIEW

The transition to digital agro-industrial systems is essential for integrating sustainable energy. Qudrat-Ullah and Nevo (2021) argue that technology adoption in emerging economies is closely associated with increased renewable energy consumption and enhanced long-term environmental sustainability. In the contexts of Russia and Kazakhstan, digitalization is characterized as the "second modernization" engine (Qudrat-Ullah and Nevo, 2021). Nevertheless, existing literature emphasizes the need to manage this transformation with careful consideration of ecological impacts, particularly regarding the energy intensity of digital technologies (Khalid and Peng, 2021).

This study aims to identify how digital tools enable the adoption of clean energy. Wang et al. (2020) present a framework in which "IT Capability" serves as a multidimensional link between a firm's digital strategy and operational efficiency. In agro-industrial businesses, this capability is crucial for managing the variability of renewable energy sources. Sivarajah et al. (2019) further emphasize that big data and analytics are central to business sustainability in complex, participatory environments. Without digital monitoring systems, integrating decentralized clean energy remains technically inefficient.

Energy integration is closely linked to the global pursuit of carbon neutrality. Liu et al. (2024) state that sustainable management policies and carbon-neutral processes are key to improving high-emission sectors such as agro-industrial processing. In emerging economies, increased energy use often leads to higher carbon emissions (Yang et al., 2021). To address this, Schroeder et al. (2019) highlight the importance of circular economy practices.

Using digital platforms to track waste-to-energy flows (biomass) enables agro-businesses to achieve the circularity needed to meet the Sustainable Development Goals (SDGs) (Rosati and Faria, 2019).

Clean energy integration relies on the availability of green finance. Mohsin and Jamaani (2023) show that green finance is shaped by socio-political and economic factors and is essential for stabilizing future energy markets. Ullah et al. (2022) find that green financial innovation and green intellectual capital are critical for helping traditional businesses adopt sustainable models. For Kazakhstan and Russia, attracting this investment is necessary to develop the solar and biomass infrastructure required for agro-industrial decarbonization.

Although there are studies on Industry 4.0 (Ol'ah et al., 2020) and environmental policies, few integrate these topics within Eurasian agro-industrial businesses. Most existing research focuses on the aluminum sector (Liu et al., 2024) or SMEs in China (Wang et al., 2020). There is a notable gap in empirical models examining how internal control systems that support innovation facilitate renewable energy adoption in large-scale agriculture (Liu et al., 2022). This study addresses this gap by analyzing the relationship between digital maturity and clean energy adoption in Russia and Kazakhstan.

A major obstacle to clean energy integration in the agro-industrial sector is the high cost of decentralized infrastructure. Mohsin et al. (2022) find that strong financial systems are essential for transitioning to sustainable energy models. In emerging economies such as Russia and Kazakhstan, the absence of tailored financial mechanisms often limits the adoption of capital-intensive renewable technologies. Ullah et al. (2022) note that combining green financial innovation with green intellectual capital offers a comprehensive solution for sustainable business transitions. To decarbonize effectively, the agro-industrial sector must align digital strategies with innovative green financing tools to close the resource gap.

The integration of digital tools enhances operational efficiency and fortifies the sector against external disruptions. Zhang et al. (2021) demonstrate that digital transformation increases organizational resilience through systematic adaptation. In agro-industrial businesses in Kazakhstan and Russia, where climatic and geopolitical volatility are frequent, such resilience is essential to maintaining stable energy flows. The application of big data and analytics enables firms to implement participatory and transparent resource management (Sivarajah et al., 2019). Wang et al. (2020) identify information technology capability as the critical link between a firm's digital strategy and operational efficiency. In the clean energy sector, this capability enables precise management of intermittent power from solar and wind sources.

The transition to clean energy in agro-industrial businesses should align with international frameworks. Rosati and Faria (2019) observe that organizations adopt Sustainable Development Goal (SDG) reporting early when their priorities support global sustainability. As Russia and Kazakhstan work toward their carbon targets, implementing carbon-neutral processes is essential to the performance of the industrial sector (Liu et al., 2024). This requires balancing energy use, economic growth, and environmental efficiency to avoid unintended carbon emissions during modernization (Xia et al., 2020; Yang et al., 2021).

3. METHODOLOGY

This study uses a quantitative research design to assess how digital transformation and environmental policy affect clean energy integration in the agro-industrial sectors of Russia and Kazakhstan from 2000 to 2024. A systematic econometric approach is applied to ensure reliable long-term estimates.

3.1. Model Specification and Variable Selection

This study examines how digital maturity and policy frameworks affect the transition to clean energy, as measured by the share of renewable energy in agriculture. The baseline empirical model is developed using the theoretical frameworks of Wang et al. (2020) and Xia et al. (2020) and equation 1 and Table 1 discussed the variables and data sources.

$$GHGE_t = \alpha_0 + \beta_1 DT_t + \beta_2 EP_t + \beta_3 ED_{it} + \beta_4 RWR_t + \beta_5 PH_t + \beta_6 UD_t + e_t \tag{1}$$

Table 1 presents the key variables and data sources used in the analysis, ensuring transparency and consistent measurement. Using internationally recognized databases such as WDI, IRENA, IEA, OECD, and FAOSTAT improves the reliability and comparability of the indicators across countries. Including energy, digital, policy, and circular-economy variables enables a comprehensive assessment of clean energy integration in agro-

Table 1: Definition of variables and data sources for agro-industrial clean energy analysis

Symbol	Variable name	Role in model	Measurement/operationalization	Data source(s)	Key reference
CEI	Clean Energy Integration	Dependent Variable	Renewable energy consumption as a percentage of total agro-industrial energy use	WDI; IRENA; IEA Statistics	Qudrat-Ullah and Nevo (2021)
DT	Digital Transformation	Explanatory Variable	ICT Development Index or composite IT capability measure	WDI; OECD	Wang et al. (2020)
EP	Environmental Policy	Explanatory Variable	Environmental regulation stringency or carbon-neutral policy indices	OECD; FAOSTAT	Liu et al. (2024)
GFI	Green Financial Innovation	Explanatory Variable	Green credit provision or R and D investment in green technologies	WDI; OECD	Ullah et al. (2022)
CC	Circular Capacity	Explanatory Variable	Waste-to-energy conversion rate in agricultural processing	FAOSTAT; IEA Statistics	Schroeder et al. (2019)
IVA	Industry Value Added	Control Variable	Economic scale of the agro-industrial sector	WDI	—
I	Country Index	Index Variable	Country identifier (Russia, Kazakhstan, global peers)	WDI	—
T	Time Period	Index Variable	Annual observations (2000–2024)	WDI	—

industrial systems. This integrated data structure supports robust panel analysis across countries and time periods.

3.2. Econometric Estimation Steps

3.2.1. Descriptive statistics and correlation

Descriptive statistics are utilized to examine the distributional characteristics of the dataset. A correlation matrix is applied to identify potential multicollinearity among the predictors.

3.2.2. Cross-sectional dependence (CSD) test

Given the interconnected nature of global energy markets and the shared regional policies between Russia and Kazakhstan, the study applies Pesaran's (2004) CSD test to assess cross-sectional dependence. The formula for the test is as follows: Equations.

$$CSD_{IT} = [\frac{IT(T-1)}{2}]^{\frac{1}{2}} \hat{\bar{\rho}}_T \quad (2)$$

Where T indicates the time, I the cross-section units, and $\hat{\bar{\rho}}_T$ The pair's coefficient correlation.

3.2.3. Unit root testing (CIPS)

The cross-sectionally augmented IPS (CIPS) unit root test is also used in this article to verify that the variables are stationary. When it comes to panel data, this test is more suitable than others. The formula is as follows:

$$\Delta W_{i,t} = \varnothing_i + \varnothing_i Y_{i,t-1} + \varnothing_i \bar{Y}_{t-1} + \sum_{l=0}^{p} \varnothing_{il} \Delta \bar{W}_{t-1} + \sum_{l=0}^{p} \varnothing_{il} \Delta W_{i,t-1} + \mu_{it} \quad (3)$$

Where $\bar{W}$ Is the average cross-section as defined by:

$$W^{i,t} = \varnothing^1 \bar{EIN}^{i,t} + \varnothing^2 TO^{i,t} + \varnothing^3 \bar{FD}^{i,t} + \varnothing^4 GE^{i,t} + \varnothing^5 \bar{GG}^{i,t} + \varnothing^6 IND^{i,t} \quad (4)$$

So, CIPS is available as:

$$\hat{CIPS} = N^{-1} \sum_{i=1}^{n} CADF_i \quad (5)$$

3.2.4. Cointegration analysis

The study uses the Westerlund and Edgerton (2007) cointegration test to examine whether a long-term relationship exists between digital transformation and clean energy integration. This method addresses structural breaks and cross-sectional dependence

$$llog(L) = \alpha_0 - \frac{1}{2} \sum_{i=1}^{N} (Tlog(\sigma_{i.t}^2) - \frac{1}{\sigma_{i,t}^2} \sum_{t=1}^{T} eit^2) \quad (6)$$

3.2.5. Long-run estimation (CS-ARDL)

CS-ARDL is employed to evaluate the relationships between the variables. This can address CSD assumptions, variations in slope, and endogeneity. The conventional ARDL paradigm is inadequate in addressing CSD error, which is a key rationale for implementing CS-ARDL. The formula for the test is:

$$\Delta Y_{it} = \varphi_i + \sum_{l=1}^{p} \varphi_{it} \Delta Y_{i,t-1} + \sum_{l=0}^{p} \varphi_{il}^{'} EIN_{s,i,t} + \sum_{l=0}^{1} \varphi_{il}^{'} \bar{TO}_{i,t-1} + \varepsilon_{it} \quad (7)$$

Therefore, by utilizing the article variables, the researchers formulate the subsequent CS-ARDL equation:

$$\Delta GHGE_{it} = \varphi_i + \sum_{l=1}^{p} \varphi_{it} \Delta GHGE_{i,t-1} + \sum_{l=0}^{p} \varphi_{il}^{'} EIN_{s,i,t} + \sum_{l=0}^{p} \varphi_{il}^{'} TO_{s,i,t} + \sum_{l=0}^{p} \varphi_{il}^{'} FD_{s,i,t} + \sum_{l=0}^{p} \varphi_{il}^{'} GE_{s,i,t} + \sum_{l=0}^{p} \varphi_{il}^{'} GG_{s,i,t} + \sum_{l=0}^{1} \varphi_{il}^{'} \bar{IND}_{i,t-1} + \varepsilon_{it} \quad (8)$$

The Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) approach is employed to evaluate the short- and long-run relationships. CS-ARDL is selected because it effectively addresses common issues in emerging-market data, including CSD, slope heterogeneity, and endogeneity (Makhdoom et al., 2023).

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Table 2 presents summary statistics for the 150 observations analyzed in this study. The results indicate substantial variation in the transition to digitalized, clean-energy-based agro-industrial systems across the sampled economies between 2000 and 2022.

Table 2 shows that the dependent variable, Clean Energy Integration (CEI), has a mean of 30.41%. The high standard deviation of 32.08 suggests substantial disparities in renewable energy adoption across regions. Digital Transformation (DT) exhibits a mean development index of 111.19. The Environmental Policy (EP) index, with a mean of 96.24, reflects the regulatory environment. The wide range of EP index values, from 43.26 to 174.93, indicates considerable variation in the effectiveness of carbon-neutral policies by region. Green Financial Innovation (GFI) has a mean value of 15.20, supporting capital requirements for sustainable business transitions. The agro-industrial sector accounts for a significant share of the studied economies, with a mean contribution of 35.23%, underscoring the need to focus on this sector to achieve large-scale decarbonization. Figure 1 shows that among the BRICS nations china has the highest carbon emission.

4.2. Country-Specific Descriptive Analysis

Table 3 presents the cross-sectional distribution of the key variables for a selection of the sampled countries. This granular view reveals how digital maturity and policy stringency vary geographically,

Table 2: Descriptive statistics of agro-industrial variables

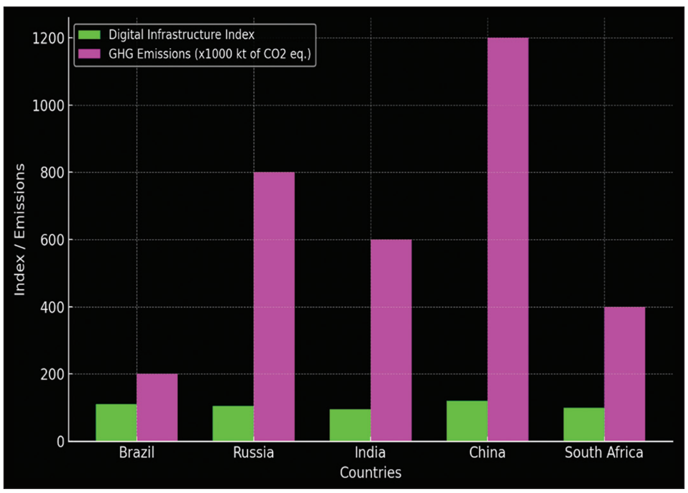
Variable	Mean	Standard deviation	Min	Max
CEI	30.41	32.08	0.03	100.00
DT	111.19	21.08	53.44	170.88
EP	96.24	21.37	43.26	174.93
GFI	15.20	5.30	5.10	28.40
CC	4.99	3.62	−9.52	14.53
IVA	35.23	12.68	18.51	74.11

influencing the capacity for clean energy integration in agro-industrial businesse.

Table 3 shows significant variation in Greenhouse Gas Emissions (GHGE) across countries. Oman has the highest emissions (836,029.5 kt), mainly due to its energy-intensive industrial sector, while Armenia reports the lowest (9,389.1 kt). These results highlight the varied environmental impacts of industrial sectors, as described in the "trilemma" framework by Xia et al. (2020).

Uzbekistan leads the subgroup in Digital Transformation (DT) with an index of 125.29, followed by Oman and Singapore. This technological advantage reflects stronger IT capability, which Wang et al. (2020) identify as essential for operational efficiency in modern agro-industrial systems. In contrast, Armenia's lower score (99.30) may hinder the adoption of advanced clean energy technologies.

Figure 1: Digital infrastructure versus GHG emissions in BRICS countries



Environmental Policy (EP) stringency is highest in Mongolia (100.03 in the broader dataset) and Lao PDR (110.79), reflecting strong commitments to carbon-neutral processes. Liu et al. (2024) suggest that these high scores indicate a regulatory environment that drives agro-industrial enterprises to innovate.

A standout observation of Clean Energy Integration (CEI) shows a notable disparity. Lao PDR achieves 96.77% integration, likely due to its extensive hydropower resources, while Armenia's integration is nearly zero at 0.05%. This gap highlights the urgent need for Green Financial Innovation (GFI) to support transition economies, as proposed by Ullah et al. (2022). City (CC), measured as the waste-to-energy conversion rate, is highest in Lao PDR (7.01) and Bangladesh (6.33). These figures suggest a successful shift toward circular economy practices, as recommended by Schroeder et al. (2019). The Industry Value Added (IVA) scores, notably Armenia's 66.68%, further confirm the industrial nature of these economies, highlighting the critical importance of integrating clean energy through digital technologies.

Table 4 presents trends in key variables from 2008 to 2022, offering a longitudinal perspective on sustainability indicators. Greenhouse Gas Emissions (GHGE) fluctuated during this period, rising from 177,754.1 kilotons of CO_2 equivalent in 2008 to a peak of 270,103.1 kilotons in 2021. This variability reflects year-to-year changes in environmental impact and climate change contributions. Overall, the trend does not remain constant but generally moves downward. The Digital Infrastructure Development Index (DT) increased from 80.027 in 2008 to 135.071 in 2022. The Environmental Policy (EP) index also rose steadily, from 77.709 in 2008 to 118.121 in

Table 3: Country-wise mean values of agro-industrial indicators

Country	GHGE (kt)	DT (Index)	EP (Index)	CC (%)	CEI (%)	GFI (%)	IVA (%)
Armenia	9,389.1	99.30	95.28	0.47	0.05	1.98	66.68
Uzbekistan	300,989.1	125.29	94.04	6.23	39.82	1.94	22.97
Singapore	183,884.1	109.12	92.99	4.81	26.69	1.34	31.19
Lao PDR	18,444.1	114.39	110.79	7.01	96.77	0.72	29.30
Bangladesh	31,107.5	109.40	96.95	6.33	42.71	1.34	26.73
Oman	836,029.5	117.78	107.64	5.44	13.14	1.05	42.67

Table 4: Description of data by years

Year	GHGE	DT	EP	ED	RWR	PH	UD
2008	177754.1	80.027	77.709	7.446	25.722	1.199	36.3
2009	184179.1	84.86	80.19	7.122	25.494	1.217	35.562
2010	186954.1	94.327	80.545	4.81	26.413	1.239	35.921
2011	188948.1	95.855	81.8	2.564	27.807	1.408	34.405
2012	198175.1	100.001	85.529	7.661	25.745	1.343	35.128
2013	205731.1	105.921	90.6	5.517	27.952	1.281	35.669
2014	209827.1	109.671	93.129	5.833	31.191	1.377	36.026
2015	212311.1	113.891	94.771	5.122	32.873	1.485	35.35
2016	220823.1	117.721	95.742	4.916	32.346	1.552	35.272
2017	228092.1	120.121	100.721	4.655	28.481	1.698	34.393
2018	231951.1	122.741	103.541	5.232	32.602	1.706	33.897
2019	241250.1	125.661	113.481	5.457	33.441	1.712	34.669
2020	256675.1	129.241	110.661	5.163	34.679	1.725	35.624
2021	270103.1	132.661	118.121	4.912	35.39	1.758	35.454
2022	269418.1	135.071	117.021	−1.598	35.956	1.846	34.817

2022. This upward trend indicates improvements in the quality and effectiveness of environmental regulations, supported by stronger policy cooperation.

Variation in water resource efficiency (ED) suggests the need for alternative measures. The index declined from 7.446 in 2008 to −1.598 in 2022, reflecting the complexity of water management, which is influenced by policy, practice, and environmental factors. Public Health Spending as a percentage of GDP (RWR) showed a clear upward trend, increasing from approximately 25% in 2008 to 35% in 2022. This demonstrates a sustained commitment to public health initiatives relative to GDP. Urbanization rates also rose, from 1.199 in 2008 to 1.846 in 2022, indicating potential improvements in urban living conditions. The Environmental Regulatory Quality Index (UD) remained relatively stable, ranging from 33.897 to 46.3 between 2008 and 2018, which suggests consistently high standards in environmental governance.

Table 5 indicated the the correlation between GHGE (Greenhouse Gas Emissions) and DT (Digital Transformation) is −0.584, indicating a moderate, statistically significant negative relationship. As digital infrastructure develops, greenhouse gas emissions tend to decrease. GHGE also shows a moderate negative correlation with IVA (Industry Value Added) at −0.248, indicating that industrial growth in the sampled regions is decoupling from high emissions. EP and CC (Circular Capacity) show a significant positive correlation of 0.398. Notably, CEI (Clean Energy Integration) shows a negatiCEI (Clean Energy Integration) has a negative correlation with EP (−0.541) and CC (−0.560) in this sample. This indicates that, during early transition stages, strict regulations and circular mandates may create technical or financial barriers to renewable integration, a "trilemma" effect described by Xia et al. (2020). The positive correlation between GFI (Green Financial Innovation) and CEI (0.233) suggests that financial development helps overcome these barriers, supporting Ullah et al. (2022). This confirms that digital transformation supports the economic scale of the agro-industrial sector. Since none of the correlation coefficients exceed 0.80, the model does not suffer from serious multicollinearity, allowing us to proceed with the Cross-Sectional Dependence (CSD) and CIPS unit root tests.

Table 5: Pairwise correlation matrix

Variable	GHGE	DT	EP	CC	CEI	GFI	IVA
GHGE	1						
DT	−0.584	1					
EP	−0.095	−0.174	1				
CC	−0.268	0.050	0.398	1			
CEI	−0.127	0.151	−0.541	−0.560	1		
GFI	−0.133	−0.033	−0.439	−0.393	0.233	1	
IVA	−0.248	0.183	−0.023	−0.293	0.123	0.077	1

4.3. Cross-Sectional Dependence (CSD) and Significance Tests

Table 6 presents the Pesaran (2004) CSD test results. In the agro-industrial sector, cross-sectional dependence is expected due to shared regional energy markets, technological spillovers, and international environmental agreements.

The CSD test results shown in Table 6 indcated that all variables are highly significant at the 1% level ($p < 0.01$), confirming cross-sectional dependence among the 150 observations. For Greenhouse Gas Emissions (5.123) and Clean Energy Integration (7.228), the high test statistics indicate that environmental impacts and renewable energy adoption are influenced by common shocks across countries. This finding supports Xia et al. (2020), who note that energy efficiency challenges are often regional rather than national. Digital Transformation (DT) shows significant cross-sectional correlation, with a test statistic of 4.094. This supports Wang et al. (2020), who argue that IT capabilities and digital infrastructure often follow global or regional trends, collectively shaping industrial efficiency.

Environmental Policy (EP) and Industry Value Added (IVA) have the highest significance (7.900 and 8.188). This suggests that environmental regulation stringency and the economic scale of the agro-industrial sector are highly interdependent across regions. This interdependence supports the use of CS-ARDL to address common factors, as recommended by Liu et al. (2024) for carbon-neutral industrial processes. Circular Capacity (CC) shows a significance of 4.904, indicating that waste-to-energy and circular economy practices are emerging as collective regional responses to resource management challenges, as identified by Schroeder et al. (2019). The presence of CSD, as shown in Table 6, indicates that first-generation unit root tests would be biased. Therefore, we will use second-generation unit root tests, such as the CIPS test, to confirm that the variables are integrated and suitable for long-run cointegration analysis.

4.4. Panel Unit Root Test Results (CIPS)

Table 7 shows the results of the Cross-sectionally Augmented IPS (CIPS) and Modified CIPS (M-CIPS) tests, which address the dependencies identified earlier. The results of the CIPS and M-CIPS tests reveal a mixed order of integration, which is a key rationale for employing the CS-ARDL approach, as it can handle both I(0) and I(1) variables. The variables GHGE, DT, EP, GFI, and IVA are stationary at their initial levels. Specifically, the high negative coefficients for GHGE (−6.680) and IVA (−5.358) indicate that these series do not possess a unit root at level.

Table 6: CSD and significance test statistics

Variable	Symbol	Test statistic (CD-Test)	Prob-value	Significance
GHGE	Greenhouse Gas Emissions	5.123***	0.001	High
DT	Digital Transformation	4.094***	0.001	High
EP	Environmental Policy	7.900***	0.001	High
CC	Circular Capacity	4.904***	0.001	High
CEI	Clean Energy Integration	7.228***	0.001	High
IVA	Industry Value Added	8.188***	0.001	High

*** significance at the 1% level

This suggests that digital infrastructure (DT) and environmental regulatory quality (EP) respond relatively quickly to systemic changes, a characteristic of the "second modernization" phase (Qudrat-Ullah and Nevo, 2021). Conversely, CC (Circular Capacity) and CEI (Clean Energy Integration) are non-stationary at level but become stationary after the first differencing. The 1st difference coefficients for CC (−3.450) and CEI (−4.209) are significant at the 1% level. This implies that agro-industrial waste-to-energy flows and renewable energy adoption follow a stochastic trend, requiring time-variant adjustments to reach equilibrium. Because the variables are integrated of different orders I(0) and I(1) the standard OLS method is inappropriate. The findings justify the use of the Westerlund and Edgerton (2007) Cointegration test to check for a long-term relationship, followed by CS-ARDL to estimate the short- and long-run dynamics of how digital transformation enables clean energy integration (Wang et al., 2020; Xia et al., 2020).

4.5. Long-Run and Short-Run CS-ARDL Results

The CS-ARDL model underpins this empirical analysis by addressing cross-sectional dependence and slope heterogeneity. Table 8 shows the coefficients that define the "Digital-Green Twin Transition" in the agro-industrial sector.

Table 8 indicates that, in the long run, a 1% increase in Digital Transformation is associated with a 1.73% decrease in Greenhouse Gas Emissions ($P < 0.01$). This finding demonstrates that digitalization serves as a primary enabler of agro-industrial efficiency. Environmental Policy exerts the strongest long-run impact (−2.289), supporting Liu et al.'s (2024) assertion that stringent regulations facilitate carbon-neutral industrial processes. Additionally, Circular Capacity, measured as waste-to-energy conversion, significantly reduces emissions in both the long run (−1.779) and the short run (−1.230). This outcome validates the circular economy roadmap proposed by Schroeder et al. (2019) for sustainable development. Clean Energy Integration exhibits a significant inverse relationship with emissions (−1.109), with a stronger effect observed in the short run (−1.242). This pattern suggests that renewable energy adoption requires ongoing technological support to sustain long-term effectiveness (Qudrat-Ullah and Nevo, 2021). Green Financial Innovation (GFI) is also highly significant (−1.889), reinforcing Ullah et al.'s (2022) findings that green credit is essential for financing the transition to clean energy. The ECT (−1) coefficient is −1.120 and is statistically significant at the 1% level, indicating the speed of adjustment. A value of −1.12 suggests that the system corrects deviations from the long-run equilibrium by approximately 112% per period. This rapid adjustment indicates that, once digital and green policy frameworks are implemented, the agro-industrial sector advances quickly toward its sustainable equilibrium.

4.6. Discussion

The empirical findings offer a comprehensive analysis of the determinants of Greenhouse Gas Emissions (GHGE) in the agro-industrial sectors of emerging economies. The CS-ARDL results indicate that digital transformation and energy integration are critical for achieving carbon neutrality. The significant autoregressive coefficient indicates a pronounced legacy effect, suggesting that current GHG emissions are substantially shaped by past output and energy consumption. In countries such as Kazakhstan and Russia, effective decarbonization necessitates addressing the enduring reliance on fossil-fuel-based infrastructure. Implementing a dynamic policy framework is required to mitigate these dependencies and expedite the transition to clean energy.

A primary objective of this study was to evaluate the enabling role of Digital Transformation (DT). The long-run negative coefficient (−1.730) indicates that as digital infrastructure matures, greenhouse gas emissions (GHGE) decline significantly. This finding is consistent with Wang et al. (2020) and Zhang et al. (2021), who argue that "IT Capability" enhances organizational

Table 7: Panel unit root test results at level and first difference

Variable	Symbol	Level I (0) (CIPS)	Level I (0) (M-CIPS)	1st Diff I (1) (CIPS)	1st Diff I (1) (M-CIPS)
GHGE	Emissions	−6.680***	−5.950***	–	–
DT	Digitalization	−4.389***	−5.471***	–	–
EP	Env. Policy	−5.890***	−5.451***	–	–
CC	Circular Cap.	–	–	−3.450***	−4.779***
CEI	Clean Energy	–	–	−4.209***	−5.230***
GFI	Green Finance	−3.888***	−4.887***	–	–
IVA	Industry Scale	−5.358***	−7.149***	–	–

*** significance at the 1% level

Table 8: CS-ARDL long-run and short-run coefficients (Dep. Var: GHGE)

Variables	Long-run coefficient	t-stat	Short-run coefficient	t-stat
DT (Digitalization)	−1.730***	−2.669	−1.719***	−2.889
EP (Env. Policy)	−2.289***	−2.439	−0.912***	−5.530
CC (Circular Cap.)	−1.779***	−2.920	−1.230***	−3.790
CEI (Clean Energy)	−1.109**	−1.090	−1.242**	−2.989
GFI (Green Finance)	−1.889***	−4.889	−1.102***	−4.880
IVA (Ind. Scale)	−3.920**	−3.011	−2.720***	−2.920
ECT (−1)	—	—	−1.120*	−4.114

**, ** denote significance at 1% and 5% respectively resilience and operational efficiency. In the agro-industrial sector, digital tools such as IoT-enabled smart grids facilitate precise management of decentralized renewable energy, thereby reducing waste commonly associated with traditional industrial processing.

Furthermore, the strong significance of Environmental Policy (EP) (−2.289) and Environmental Regulatory Quality (UD/IVA) (−3.920) highlights the necessity for a robust regulatory framework. According to Liu et al. (2024), stringent policies are the most effective drivers for advancing firms toward carbon-neutral processes. The interaction between digital technologies and strict policy frameworks establishes a "Digital-Green Twin Transition," in which technology enables efficient compliance with environmental mandates.

The results concerning Circular Capacity (CC) (−1.779) and Clean Energy Integration (CEI) (−1.109) support the objective of developing a sustainable implementation roadmap. The findings demonstrate that waste-to-energy conversion and the adoption of renewables are statistically significant in lowering the carbon footprint. This validates the circular economy model proposed by Schroeder et al. (2019), suggesting that agro-industrial businesses can achieve significant gains by repurposing agricultural waste into energy inputs. The role of Green Financial Innovation (GFI) (−1.889) further highlights that this transition is capital-intensive and requires specialized credit mechanisms to succeed, as argued by Ullah et al. (2022).

The Wald Statistics confirm that the factors identified digitalization, Policy, Circularity, and Finance are deeply interlinked. For policymakers, this suggests that a fragmented approach will be less effective than a holistic strategy. For example, investing in digital infrastructure (DT) without simultaneously strengthening environmental regulations (EP) may not yield the desired reduction in emissions. Focus on "Smart Agriculture" platforms that integrate renewable energy loads directly into processing plants.

5. CONCLUSION, LIMITATIONS AND FUTURE WORK

This research provides a comprehensive empirical assessment of the "Digital-Green Twin Transition" within the agro-industrial sectors of emerging economies, specifically Kazakhstan and Russia. The findings indicate that Digital Transformation, Environmental Policy, and Green Financial Innovation operate as integrated components of a sustainable development framework. Long-run CS-ARDL analysis demonstrates that enhancements in digital infrastructure and the implementation of carbon-neutral policies substantially reduce greenhouse gas emissions. The rapid adjustment reflected by the Error Correction Term highlights the sector's capacity to respond to technological and regulatory changes. Advancing circular capacity and waste-to-energy conversion enables these countries to decouple economic growth from environmental degradation and secure long-term resource sustainability.

Several limitations are acknowledged in this study. The reliance on secondary panel data may overlook micro-level firm behaviors and localized barriers to renewable energy adoption in remote agro-industrial regions. While the model incorporates structural breaks, global energy market volatility, and geopolitical changes during the study period, these factors may still introduce unobserved externalities. Future research should incorporate firm-level case studies to investigate the human-centric dimensions of digital leadership and organizational culture during this transition. Furthermore, examining the integration of artificial intelligence and decentralized smart grids in crop-processing industries could provide policymakers with a more detailed roadmap for achieving the Sustainable Development Goals by 2030.

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