Anti-corruption, Digital Economy Development and Carbon Emissions - An Empirical Study Based on 121 Countries Worldwide

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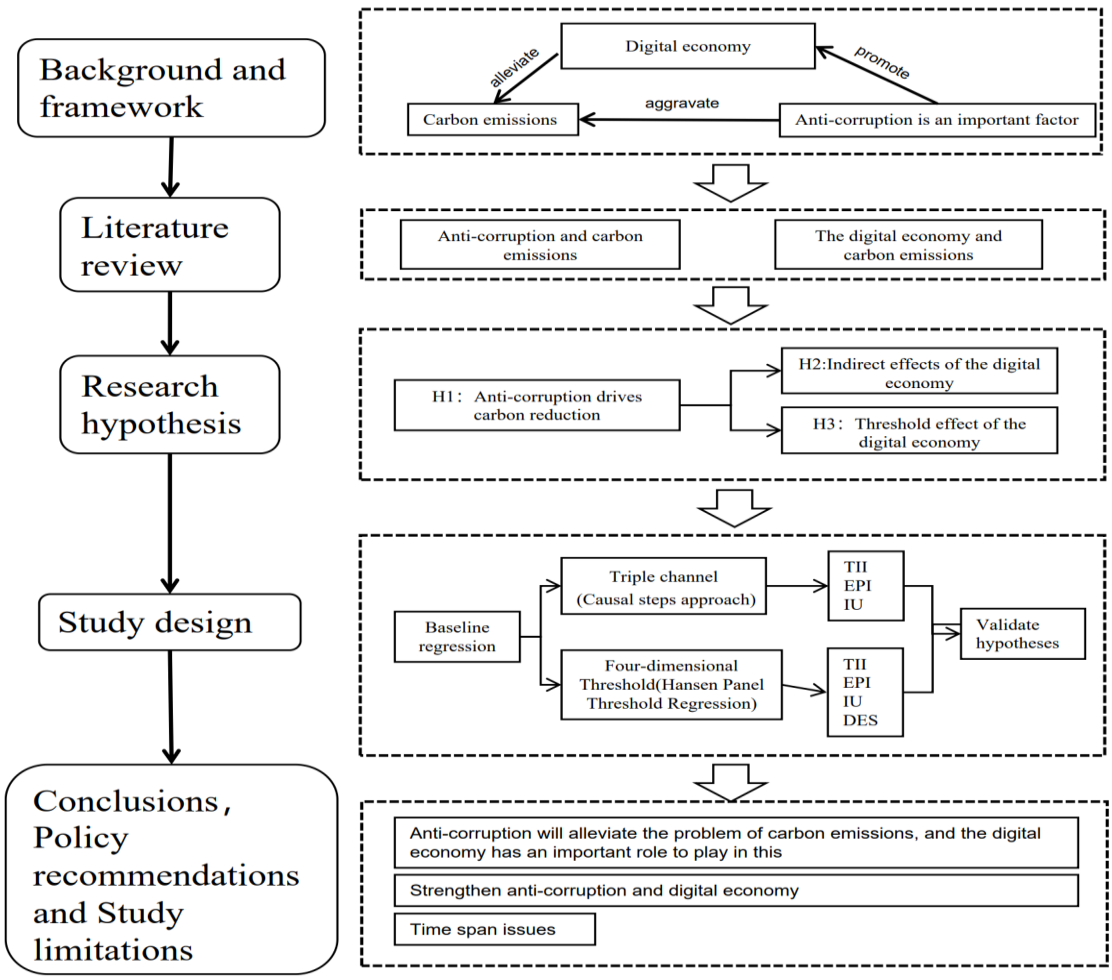
Graphical abstract



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Abstract

At a time when excessive carbon emissions(CE) lead to rapid global warming, anti-corruption(ACP) has become an important initiative to reduce CE. Meanwhile, the growth of the digital economy (DE) can also have a substantial impact on the connection between ACP and CE. Utilizing panel data from 121 countries across the globe spanning the years 2013 to 2021, this paper empirically investigates relationship between ACP, the development of the DE and CE. The overall impact of ACP on CE reduction and the threshold effect of DE development during the reduction by ACP are analyzed using the stepwise regression method and the panel threshold model. Research indicates that (1) ACP plays a crucial role in reducing CE, as confirmed by various robustness tests. (2) ACP can effectively reduce CE by promoting the DE, particularly through e-participation and the Internet. (3) With DE development, the inhibitory effect of ACP on CE shows a significant threshold effect. ACP exhibits more significant CE reduction effects in countries with a higher level of DE. (4) Heterogeneity analysis shows that the relationship between ACP and CE varies across continents and between colonized and non-colonized countries. This is because low levels of economic development and colonial history may distort the relationship. These findings provide recommendations for governments to utilize the DE to strengthen ACP initiatives, facilitate achieving global sustainable development goals and reduce CE.

Keywords: anti-corruption, carbon emissions, digital economy, threshold effect

1. Introduction

According to the Climate Change 2023, released by the United Nations Intergovernmental Panel on Climate Change (IPCC) in 2023 (AR6 Synthesis Report: Climate Change 2023), human activities are currently contributing an average global warming of 1.1ºC. The Emissions Gap Report 2024 (2024) has also projects a median global warming of 3.1ºC by 2100 under current policy pathways, with a probability of 66%, and a probability of 1.5ºC of warming of close to 0%, well above the target of the Paris Agreement. This means that the average annual carbon reduction required globally over the next decade would need to be 7.5%. The report also points out that issues such as stagnant progress in nationally determined contributions (NDC) and gaps in the implementation of carbon reduction policies in various countries. In addition, the International Energy Agency's World Energy Outlook 2024, published in the same year, has also pointed out that although the total amount of clean energy deployment is currently increasing globally, it has not yet offset the growth in fossil fuel consumption. Therefore global carbon emissions(CE) situation is grim, along with the challenging task of reducing emissions. It is extremely important to manage CE more effectively.

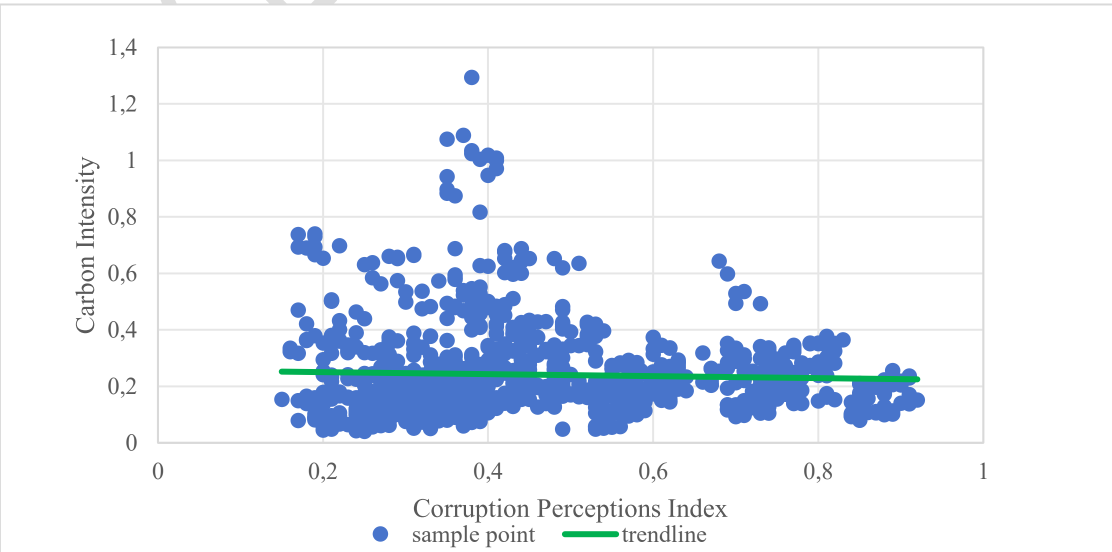

Figure 1. Scatterplot of the Corruption Perceptions Index-Carbon Intensity for 121 countries

Data source:Transparency International,World Bank.

Previous research concerning the environment and CE has been sufficiently thorough and extensive, yet the majority of these studies have centred on natural factors. However, the issue of CE is not solely an environmental concern; some economic and political factors can also significantly impact the emissions, with corruption being a major factor (Reza et al., 2019). In recent years, corruption has inflicted considerable environmental damage worldwide. For instance, in Brazil, corruption has led to infrastructure projects engaging in unrestrained, environmentally destructive development. Meanwhile, certain Western multinational corporations have bribed local government officials in Africa to secure development privileges that disregard environmental protection. Corruption is often described as the misuse of authority for individual or corporate benefit (Gorsira et al., 2018). It tends to dissipate the impact of environmental regulation and increase energy consumption and CE. Corruption can also lead firms to avoid environmental regulation or environmental taxes by bribing officials, thus indirectly exacerbating CE and environmental problems (Zhang, 2024). In addition, corruption can undermine the mechanisms of economic systems, delaying the environmental Kuznets curve (EKC) inflection point (Reza et al., 2019). This implies that countries with lower levels of anti-corruption(ACP) will achieve CE reduction later than those with higher levels of ACP. Therefore, ACP becomes particularly important for reducing CE and mitigating CE problems. We analyzed the global trend of ACP and CE in recent years, proving the above relationship. Based on the carbon intensity of each country published annually by the World Bank and the global corruption perception index (CPI) published annually by Transparency International, a scatter plot of the anti-corruption index and carbon intensity of 121 countries from 2013 to 2021 was created (Figure 1). Figure 1 shows that the integrity index was negatively correlated with CE over the nine years,countries with high carbon emissions tend to have low CPI indices, while countries with high CPI indices tend to have low and concentrated carbon emissions. This indicates that ACP has an important role in mitigating CE.

Existing research on ACP and CE mainly focuses on traditional mechanisms such as environmental regulation and resource allocation efficiency. In today's swiftly evolving digital economy (DE), what function does the DE serve in the connection between ACP and CE? However, literature on this issue is rare. The 2024 Digital Economy Report, released by the United Nations Conference on Trade and Development (UNCTAD,2024), states that e-commerce sales in countries accounting for about three-quarters of the global economy have grown by nearly 60% in the past decade. This also proves that information and communication technologies (ICT) are now playing a key role in the digital revolution across industries with their high penetration rate (Hao et al., 2022). The swift advancement of the DE can enhance the industrial efficiency and energy usage, significantly aiding in the reduction of CE. (Ahmed et al., 2021; Hao et al., 2022). The DE can also advance carbon peaking by driving economic development (Lyu et al., 2023). In addition, ACP can promote digital innovation by facilitating adequate internal and external communication to enhance corporate transparency (Park et al., 2021). The advancement of the DE across all sectors of the nation, particularly its impact on the political sphere, has proven beneficial in combating corruption and environmental issues. Concurrently, large models and deep learning derived from DE can also provide relatively accurate predictions of climate and environmental conditions. Relying on sound forecasting facilitates differentiated temporal and spatial approaches to addressing carbon emissions (Jasmine et al., 2025 ; Nirmal et al., 2025). Thus, ACP can enhance CE reduction by creating a market environment conducive to DE development. This means that ACP can reduce CE by promoting DE development, and DE development can promote ACP to alleviate CE issues. Therefore, this paper aims to explore what positive changes the new developments and applications of the digital economy can bring in an era where carbon emissions and corruption issues are becoming increasingly severe. DE has developed relatively rapidly over the past decade or so, whilst data from 2013 to 2021 is comparatively comprehensive. Extracting relevant data from this period facilitates detailed research. Concurrently, given that the impact of DE on corruption and CE varies significantly across nations worldwide, efforts have been made to encompass the majority of countries and regions globally to enable differential analysis based on varying variables. Based on the global panel data of 121 countries from 2013 to 2021, this paper investigated the relationship between ACP, CE and the DE using stepwise regression and other methods. We sought to address the questions of how ACP's effects on CE evolve and whether the swift expansion of the DE will amplify ACP's role in reducing CE, given the critical global CE scenario and the rapid growth of DE trade.

2. Literature Review

2.1 Corruption and CE

Corruption and carbon are topics of increasing interest in the fields of environmental economics and sustainable development. Corruption can affect CE through many channels, which is most evident in the channels of ecological environmental protection, industrial production, economic development, resource allocation, policy implementation efficiency and environmental regulation. In terms of ecological environmental protection, Asif et al. (2023) and Rahman et al. (2022) analyzed the relationship between corruption, political instability and environmental degradation from a regional comparative perspective. They concluded that corruption enhanced CE (especially regarding carbon and ecological footprints). In terms of industrial production, Wang et al. (2023) and Pei et al. (2021) analyzed the effect of corruption and energy efficiency on industrial CE at the industrial level and found that increased corruption promoted industrial CE. In terms of economic development, Zhang (2016) analyzed the direct and indirect effects of corruption and CE over 20 years in the Asia-Pacific Economic Cooperation (APEC). It was found that corruption reduced gross domestic product (GDP) per capita and exacerbated the CE problem by delaying the inflection point of the EKC through hindering economic development. In terms of resource rationalization, Xie et al. (2023) examined how corruption and resource misallocation affect CE, noting that corruption may lead to resource misallocation, thus increasing CE. In terms of policy implementation efficiency and environmental regulation quality, Zhang (2024) argued that corruption dissipated the effects of environmental regulations, thereby increasing pollution emissions. Chen (2018) argued that the increase in the proportion of government officials with corrupt behavior weakened environmental regulation effectiveness and promoted carbon and other pollution emissions, confirming the above conclusion. Meanwhile, Wang et al. (2023) and Rui et al. (2023) also emphasized the importance of corruption governance in reducing CE. ACP will act as a curb on corruption, which is conducive to alleviating the CE problem. He et al. (2024) examined the moderating effect of ACP between government environmental objectives and enterprise green innovation. They found that higher levels of ACP facilitated enterprise green innovation and CE reduction.

In summary, corruption has a positive impact on CE. Therefore, promoting ACP is an important initiative to mitigate the CE problem.

2.2 DE and CE

The relationship between the DE and CE has increasingly been studied. It has been found that the effect of the DE on CE has both positive and negative impact directions, involving the levels of enterprises and cities. In terms of positive impacts, Salahuddin et al. (2015) suggested that DE development may significantly increase the need for electronic devices, which in turn increases electricity consumption and indirectly leads to higher CE. However, more studies have reported that the DE has a negative effect on CE. For example, Liu (2023) suggested that the DE played a crucial role in enhancing high-quality economic growth by reducing the intensity of CE, accelerating the EKC inflection point. At the enterprise level, Wang et al. (2024) studied the impact of the DE on low-carbon innovation under CE trading using methods such as DID modeling and moderating variables. They argued that the DE was a key low-carbon innovation resource and had a positive moderating effect on low-carbon innovation. At the city level, Li et al. (2024) analyzed the impact of the DE on CE efficiency in 283 Chinese cities. The results show that the DE exhibited positive impacts and spatial spillovers on green technological innovations and energy structure optimization, which is conducive to improving efficiency of CE. Li et al.(2024) analysed the relationship between digital finance and urban green economies across 278 Chinese cities over a nine-year period. Findings indicate a medium U-shaped relationship between digital finance and carbon co-governance efficiency. The carbon reduction effects of digital finance and DE in non-resource cities became more pronounced after 2015. Overall, developing the digital economy serves as a crucial tool for promoting pollution reduction and carbon mitigation.

2.3 Research Gaps and Limitations

In the literature on corruption and the impact of ACP on carbon emissions, existing research on the mechanisms by which corruption or ACP affects CE in traditional areas such as environmental regulation, resource allocation, and economic development is already quite comprehensive. However, there is still a lack of research on the mechanisms by which ACP combined with DE affects CE. Traditional models in the relevant literature predominantly employ conventional control variables such as GDP or urbanisation rates, failing to incorporate DE and its associated indicators. Even studies that acknowledge DE's influence typically treat it merely as one control variable within multiple regression analyses. Moreover, the threshold and mediation analyses conducted within these frameworks often focus on indicators like the HDI that emphasise economic development. This approach proves inadequate for effectively demonstrating DE's specific impact mechanisms on political and environmental domains, nor does it elucidate its effects across different developmental stages. Few studies have focused on the impact of the rapid development of the DE on the overall relationship between ACP and CE. At the same time, most of the studies are based on cities, provinces, local areas or dozens of countries. There are few studies covering hundreds of country samples from a global perspective. Thus, it is difficult to conclude with global universality and national differences.

2.4 Contribution of This Study

This research seeks to address the gap in current studies regarding the link between ACP and CE amid the swift evolution of the DE. The innovations of this paper are as follows: (1) Current studies have mainly focused on the impact of traditional channels of corruption on CE, which is an emerging channel. This study employs a structural equation modeling framework to empirically examine the intermediary transmission mechanism through which the DE operates as a catalytic channel in translating anti-corruption policies ACP into measurable CE mitigation outcomes. Utilizing a three-path mediation analysis, the research specifically investigates how DE development, characterized by enhanced digital infrastructure deployment and e-governance adoption, functionally bridges the causal relationship between institutional integrity reforms and decarbonization performance across heterogeneous national contexts, particularly exploring how ACP affects CE through DE channels such as telecommunication infrastructures, e-participation and the Internet. This addresses the gap in the literature regarding the lack of research on digital economic mechanisms. (2) Due to the differences in telecommunication infrastructure, e-government and digital infrastructure among countries, ACP by the DE has a threshold effect on CE under the DE development level in different countries. Therefore, a threshold model is developed to comprehensively explore how the DE affects the relationship between ACP and CE. Further, this paper also analyzes in depth the direction and extent of the impact of the DE based on four threshold variables: telecommunication infrastructure, e-participation, level of Internet development and level of DE integration, It was found that the emission reduction effect of anti-corruption measures only significantly increased when DE levels exceeded specific thresholds, this not only provides policymakers with accurate references on key thresholds for DE development, but also deepens understanding of the complex and multidimensional impacts of DE, and provides new perspectives and insights for research in related fields. (3) This paper extends beyond the analysis limited to a certain country or region. The research object involves 121 countries with different development levels on a global scale from 2013 to 2021. This global sample can help to clarify the universality and differences in the relationship between ACP and CE. Thus, The study found that the impact of anti-corruption measures on carbon emissions was more pronounced in Africa and Europe, and even showed a positive correlation in countries with a colonial history, revealing the underlying regulatory mechanisms of institutional context and economic stage on emission reduction outcomes.

3. Theoretical Mechanisms and Research Hypotheses

3.1 Impact of ACP on CE

In terms of environmental protection regulations, corruption, due to its political characteristics, can bring about behaviors such as rent-seeking, bribery and harboring. These behaviors can directly impact environmental legislation and environmental law enforcement (Quah, 2006). ACP initiatives can strengthen environmental regulations, regulating the effectiveness of market instruments (such as carbon pricing) through the ability to curb rent-seeking behavior and ensure the credibility of policy commitments (Kerekes, 2011). For example, France enacted the Sapin II Act in 2017, which includes restrictions on corporate environmental regulations. At the same time, ACP also plays a role in encouraging innovation. ACP can enhance the transparency of fiscal subsidies, enabling them to fully incentivize corporate innovation and improve operational efficiency. Following the anti-corruption campaign in 2012, energy-intensive enterprises in China saw a significant reduction in opportunities to obtain exemptions from environmental policies through bribery. Meanwhile, green R&D investment and R&D expenditure both increased. An important reason for this development was that the anti-corruption campaign optimized resource allocation and the institutional environment(Chen et al., 2022). The environmental policies promoted by the ACP, such as low-carbon cities, can also enhance the efficiency of coordinated governance of carbon emissions and smog(Li et al., 2022). In addition, ACP can rebuild the bridge of communication and cooperation between the government and the market, which can enable government resources to be allocated in a scientific and effective manner (Tacconi et al., 2020). This will not only help optimize the market environment, but also have a positive impact on production efficiency and green technology innovation (He et al., 2024).

Therefore, this paper proposes hypothesis H1.

Hypothesis H1: ACP can directly promote CE reduction

3.2 Analysis of the mediating effect of the DE in the process of ACP affecting CE

ACP can certainly promote CE reduction by restraining government behavior and creating a healthier market and corporate innovation environment. However, with the rapid development of the DE, new digital political governance businesses emerge, such as e-government and digital government. The empowerment of the DE by ACP can also be a new pathway to impact carbon reduction. The impact of ACP on the DE is mainly reflected in the interaction between the government and DE-related enterprises. The interaction can be divided into corruption and ACP supporting behaviors and enterprise regulation behaviors. In the supporting behaviors, the government is more inclined to support firms that can bribe or from which they can get hidden benefits because of corruption. Consequently, the government generally provides insufficient support for enterprise innovation behavior in the market. As a result, ventures engaging in radical technological experimentation exhibit probability of bureaucratic veto power activation, particularly when innovation trajectories challenge incumbent state-owned enterprises' market dominance. This raises enterprise transaction costs, worsens the market environment and discourages enterprises from digital innovation (Bardhan, 1997). From the perspective of firms, in a corrupt business environment, firms need to spend more on bribery to get policy support, thus inadvertently reducing the cost of other activities, such as production and research and development. This not only hinders efficient enterprise resource allocation and undermines the trust relationships within the firm or between the firm and the government, which in turn hinders innovative behaviors such as DE development (Paunov, 2016). In the regulation behaviors, corrupt governments can use their regulatory prerogatives to increase the pressure on multinational firms' telecommunication industry and telecommunication infrastructure projects to enter the country in order to safeguard their interests. As a result, multinational firms are forced to use alternative entry strategies to cope with corruption. This can increase the process and difficulty of entry into projects related to the DE, thus impacting the DE process of the country (Uhlenbruck et al., 2006). Thus, ACP undoubtedly has a positive contribution to digitalization. Higher levels of ACP can enhance communication within and outside the firm and thus knowledge transfer, contributing to digitalization (Park et al., 2021).

Overall, the DE can reduce CE through both direct and indirect effects (Zuo et al., 2024). In terms of direct effects, the DE can optimize production processes and prediction accuracy to reduce excess CE. For example, companies adopting the Internet of Things (IoT) can monitor production in real time by deploying sensors in the production chain. Based on the data collected by these sensors, companies can intelligently adjust resource use and operational parameters to save resources and reduce CE (Wang et al., 2024). Integrating IoT technology with deep learning can enhance the accuracy of urban air pollution forecasting, thereby optimising energy systems, supporting environmental regulation, and aiding carbon reduction initiatives (Mohandas et al., 2025). DE can indirectly influence CE by altering the energy structure, promoting industrial advancement, and fostering the development of new technologies. In terms of energy structure, enterprises can optimize energy structure and promote energy transition and thus CE reduction by applying Internet technologies to energy production (Shahbaz et al., 2022). In terms of industrial upgrading, the application of DE-related technologies to traditional industries can accelerate industrial upgrading and indirectly reduce CE (Lyu et al., 2023). In addition, DE development has spawned artificial intelligence (AI) to promote CE reduction. AI can improve the intelligence level of the renewable energy industry, enhance energy efficiency by integrating various information during production (Boza et al., 2021) and bring significant financing to the energy industry (Tanveer et al., 2021). Thus, this paper proposes hypothesis H2.

Hypothesis H2: ACP will reduce CE by promoting the DE, such as enhancing telecommunication infrastructure construction, e-participation and Internet infrastructure construction.

3.3 Analysis of the threshold effect of the DE on the relationship between ACP and CE

ACP can promote CE reduction by optimizing resource allocation and market environment. However, nowadays, the DE is penetrating into all aspects of society. The DE can optimize the channels through which ACP acts on CE using digital communication technologies and Internet technologies, thus amplifying the effect of CE reductions. In general, The integrative application of digital technologies potentiates the emission-abatement efficacy of corruption control mechanisms, operating through direct institutional interventions and indirect market incentive realignments. The direct role is mainly reflected in the enhancement of government information transparency and online exposure-based supervision. The in-depth application of ICT can enhance the transparency of various governmental behaviors. This can free various operations from dependence on human resources (Shim et al., 2008), thus reducing corruption caused by human intervention. From a democratic perspective, power in society can be more decentralized and held in the hands of the people when they have access to information through more channels (Soper, 2007). For example, e-government can integrate government information into the Internet and make it available to the public. This can allow government operations to take place under public scrutiny and curb the growth of corrupt behavior. The popularity of the Internet enables information to spread extremely rapidly. Once corruption occurs, it can easily attract attention on the Internet. This online exposure and the ensuing pressure of public opinion greatly increase the difficulty of concealing corrupt behavior (Adam et al., 2021). The indirect effect is reflected in the fact that rapid DE development has spawned Internet education, which in turn indirectly promotes ACP. For example, in the field of higher education, the DE has brought about infrastructure optimization. Teachers can utilize online platforms to upload high-quality teaching videos, while students can study online without spatio-temporal constraints. This learning mode can reduce the cost of acquiring knowledge and stimulate students' enthusiasm for learning through diversified teaching resources and interactive methods, significantly improving teaching efficiency and effectiveness in higher education (Ruiz et al., 2020). With the widespread and deep application of the DE, ACP can be implemented more efficiently. This can also amplify the role of ACP in reducing CE. Therefore, this paper suggests that the difference between high and low levels of the DE has a threshold effect on the CE process in an ACP environment. Hypothesis H3 is proposed based on the above mechanism.

Hypothesis H3: There will be a threshold effect of ACP on CE under different levels of DE development.

4. Research Design

4.1 Model setting

4.1.1 Benchmark regression model

Drawing on the research of Zhang (2024), This study uses stepwise regression for benchmark regression. Stepwise regression can first avoid the high correlation between control variables, while intuitively demonstrating the stability of correlation coefficients, making it easier to understand the direct relationships between variables. Therefore, this study constructed the following model:

$$co_{2it} = \beta_0 + \beta_1 ACP_{it} + \beta_2 control_{it} + \pi_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where co_{2it} represents the CE intensity of country *i* in year *t*; ACP_{it} represents the degree of ACP in country *i* in year *t*; $control_{it}$ represents each of the control variables, including energy use per capita (EU), GDP per capita (GDP), trade openness (OP) and degree of urbanization (UR); β_0 is a constant term; β_1 is the estimated coefficient on the core explanatory variable; π_i is a country-fixed effect; γ_t is a year-fixed effect; ε_{it} is a random error term.

4.1.2 Modeling of channel mechanisms (mediating effects)

In order to test hypothesis H2, this paper tested each channel based on the stepwise method (Baron et al., 1986) and the method by Wen et al. (2014): the first step is to use the degree of each mediating variable as a dependent variable to test whether ACP will have an impact on telecommunication infrastructure construction, e-government and digital infrastructure construction, which represent the DE; the second step is to use CE as a dependent variable and substitute each mediating variable into the model to elucidate whether the DE will impact CE. The stepwise method can independently detect the impact mechanisms on each digital economy path, which can avoid the interference of unobservable heterogeneity when dealing with large samples in this study. The following models were constructed:

$$M_{it} = \phi_0 + \phi_1 ACP_{it} + \phi_2 control_{it} + \pi_i + \gamma_t + \delta_{it} \tag{2}$$

$$co_{2_{\mathrm{it}}} = \tau_0 + \tau_1 ACP_{it} + \tau_2 control_{it} + \tau_3 M_{it} + \pi_i + \gamma_t + \mu_{\mathrm{it}} \tag{3}$$

where M_{it} represents the channel variables representing the DE, including telecommunication infrastructure construction (TII), e-participation (EPI) and Internet level (IU); ϕ_1 represents the extent to which the core explanatory variable (the degree of ACP) affects the DE; ϕ_0 is a constant term; δ_{it} is a random error term; τ_1 represents the coefficient of the impact of ACP on CE; τ_3 represents the extent to which ACP affects CE through each DE channel; τ_0 is a constant term; μ_{it} is a random error term.

4.1.3 Threshold effect model

In order to verify whether the DE has a threshold effect during CE reduction by ACP, this paper studied the threshold effect of the DE from four aspects, namely, telecommunication infrastructure construction, e-government, telecommunication infrastructure and DE synthesis. The theory of innovation diffusion suggests that new technologies must reach a certain penetration threshold before they can bring about systemic change (Rogers,2019). Therefore, the threshold effect analysis is used to assess the impact of the digital economy in order to avoid subjective judgments on the level of digital economic development in various countries while ensuring that the research methodology is consistent with innovation diffusion theory. This method also allows for a thorough analysis of the turning points in digital economic development. This paper constructed the following single-threshold model:

$$\begin{gathered} co_{2it} = \partial_0 + \partial_1 ACP_{it} \times I(dig_{it} \leq \theta) + \partial_2 ACP_{it} \times I(dig_{it} > \theta) + \\ \partial_3 \mathrm{control}_{it} + \pi_i + \gamma_t + \sigma_{it} \end{gathered} \tag{4}$$

where I represent the threshold function; dig_{it} represents the degree of DE development, specifically including DE infrastructure construction (TII), e-participation (EPI), Internet development level (IU) and the comprehensive level of the digital economy synthesis (DES); θ represents the estimation threshold; ∂_1 and ∂_2 are the estimated coefficients of ACP and CE at each threshold level, respectively; ∂_3 is the estimated coefficient of each control variable and CE; ∂_0 is a constant term; σ_{it} is a random error term. The empirical evidence can be expanded to multi-threshold based on Eq. (4), and the appropriate number of thresholds can be selected.

4.2 Data description and sources

Limited by data availability and differences in the time caliber of data across countries, this paper selected panel data from 121 countries worldwide during 2013-2021 as the research object. These countries span all continents in the world except Antarctica to cover the globe as extensively as possible. In order to ensure sufficient objectivity and breadth, the average carbon dioxide (CO_2) emissions and GDP of these countries accounted for about 82.3% of the global average CO_2 and about 84.7% of the global average GDP during the sample period, respectively. Relevant data were mainly obtained from the World Bank database, the United Nations database and other international organizations. Indicators representing the degree of ACP were from the Corruption Perceptions Index (CPI) published annually by Transparency International. The data related to per capita energy use were collected from the database of the U.S. Energy Information Administration (EIA). In order to simplify the calculation and standardize the data, the Global Integrity Index represented the degree of ACP; foreign direct investment (FDI) represented the openness as a percentage of the national GDP; the ratio of the urban population to the national population represented the degree of urbanization, which was divided by 100; energy use per capita was divided by 10,000; GDP per capita was taken as a logarithmic number. Missing data were linearly interpolated, and data released in alternate years underwent average interpolation. Specific variables were explained below:

4.2.1 Explained variables

Referring to the methods of Pan et al. (2019), Emirhan et al. (2020) and Bolton et al. (2021), this paper used carbon intensity(CO_2 emissions per unit of GDP) as the explanatory variable of CE (CO_2). This choice aims to strip out the impact of economic scale and directly reflect emission reduction efficiency. This is because economic development is one of the most important factors affecting CE, ACP and the DE.

4.2.2 Core explanatory variables

Referring to Gisladottir et al. (2021), Rodriguez et al. (2019) and Agata (2013), this paper selected the CPI as the core explanatory variable. The CPI is also a more common indicator in ACP research, which can illustrate the degree of ACP in a country more convincingly.

4.2.3 Control variables

In the control variables, GDP represents influence of economic growth on CE. Economic growth has a significant impact on a country's CE. Scholarship on ecological modernization reveals a phased transition: the carbonization phase gives way to decarbonization phase upon surpassing critical institutional and technological capacity thresholds. Economic development in the early stage will rely on low-end industries, increasing CE. Later economic growth will increase high-end industries and industrial transfer to pass the CE inflection point, reducing CE (Grossman et al., 1992). EU is measured by per capita energy use since EU is related to the productivity level of a country and has a direct response to economic development level and environmental regulation strength (Wang et al., 2008). Openness (OP) is measured using FDI as a percentage of GDP. FDI has a complex and profound impact on CE and can drive industrial transfers or attract inward investment to increase industrialization, thus impacting CE (Zhang et al., 2023). Urbanization Rate (UR) is expressed as the percentage of urban population. The impact of urbanization on CE is also significant. Urbanization leads to rapid industrialization, which can significantly exacerbate CE (Wang et al., 2021).

4.2.4 Mediating variables

Referring to Sridhar et al. (2008), Romel et al. (2018) and Zuo et al. (2024), this paper used the telecommunication infrastructure index (TII), the e-participation index (EPI), and the number of Internet users per 100 people (IU), which are published centrally by the World Bank every year, as mediating variables indicating the degree of DE development. TII can reflect the level of digital infrastructure construction in a country in terms of digital base stations and broadband. EPI can reflect the degree of e-government in terms of the digitalization development level of a country's political governance. IU can directly reflect the degree of use of digital virtual services (such as the Internet) in a country. This provides a more comprehensive representation of the role of ACP in the DE from three different perspectives.

4.2.5 Threshold variables

Referring to Zuo et al. (2024) and Ran et al. (2023), this paper used the telecommunication infrastructure index (TII), the e-participation index (EPI), the number of Internet users per 100 people (IU) and the DE synthesis index (DES) as the threshold variables indicating the degree of DE development. This paper integrated the fixed broadband subscription ratio (FB), the fixed telephone subscription ratio (IT), the total number of mobile cellular subscriptions (GSM), ICT product exports as a percentage of total product exports (ICTP), ICT service exports as a percentage of total service exports (ICTS), the number of secure Internet servers per million people (SI) and the number of digitally interactive services as a percentage of total service exports (DD), which are published annually by the World Bank, as well as the E-Government Development Index (EDGI) published by the United Nations. These indicators were standardized and averaged to obtain the DES(see "Appendix"). This composite indicator can reflect the development of core production factors of the DE (Xia et al., 2024). ACP can impact CE mainly through physical construction outcomes such as infrastructure development, e-government and the Internet using the DE as a mediator, and plays a minor role at the level of core production factors. However, in terms of the overall relationship of the DE with ACP and CE, the development of core production factors can reflect the depth of the integrated application of the DE in political governance, digitalization and other areas. Incorporating this variable into the threshold effect analysis can enable a thorough examination of how the DE influences the connection between ACP and CE.

Table 1. Descriptive statistics of variables

Type	Variable	Hidden meaning	Average value	Standard error	Minimum	Maximum
	ACP	Corruption Perceptions Index	0.45	0.01	0.15	0.92
	CO_2	Kilograms of CO_2 emitted per dollar of GDP	0.24	0.00	0.04	1.29
	GDP	GDP per capita	8.66	0.04	5.57	11.61
	OP	Foreign direct investment, net inflows as share of GDP	0.05	0.00	-0.42	2.23
	EU	Energy use per person(kWh per person)	2.88	0.12	0.02	24.57
	UR	Share of the population living in urban areas	0.61	0.01	0.11	1.00
	EPI	E-Participation Index	0.46	0.01	0.02	1.00
	TII	Telecommunications infrastructure index	0.37	0.01	0.01	1.00
	IU	Share of the population using the Internet	53.77	0.92	1.15	100.00
DES	*FB*	Fixed broadband subscription(per 100 people)	13.74	0.42	0.00	48.79
	IT	Fixed telephone subscription(per 100 people)	5.17	3.22	-1.92	12.53
	GSM	Mobile cellular subscriptions(per 100 people)	109.69	1.01	13.49	221.31
	ICTP	ICT goods exports(% of total goods exports)	3.33	0.21	0.00	50.86

ICTS	ICT service exports(% of total service exports)	9.68	0.34	0.00	61.45
SI	Secure internet servers(per 1 million people)	4.33	2.22	-3.97	10.19
DD	Exports of digitally deliverable services as a percentage of total services exports(%)	27.18	0.64	1.34	89.02
EGDI	E-Government Development Index	0.28	0.01	0.01	0.86

4.3 Computational Environment and Software

To ensure the reproducibility and computational efficiency of our empirical analysis, all data processing and econometric estimations were conducted on a high-performance workstation.

All statistical analyses were performed using Stata/MP 17.0. Specifically: The baseline regressions and mediation effects were tested using the built-in `regress` and `xtreg` commands with robust standard errors. The panel threshold model was estimated using the `xthreg` command with bootstrap set to 500 replications. The instrumental variable (2SLS) estimations were conducted using the `ivreg2` command. Data cleaning and preliminary analysis were assisted by Microsoft Excel 365 and Stata. All relationship figure were created using Microsoft Excel 365 and Python-related programmes. The datasets were stored and processed locally on an encrypted SSD to ensure security and fast access.

5. Benchmark regression analysis

This paper utilized stepwise regression to sequentially increase the introduced control variables in order to deal with multicollinearity and improve model efficiency.Table 2 presents the results of the benchmark regression analysis of the ACP degree on CE. For the core explanatory variables (Table 2), With the addition of other variables, the absolute value of the ACP coefficient increased slightly, and its significance level rose to 5% in Models 2 and 5, while remaining at 10% in Models 3 and 4. At the same time, the regression coefficients in all models were significantly negative at a level of 10% or higher.. This indicates that ACP had a negative effect on CE, i.e., ACP reduced CE and mitigated the CE problem. This supports the conclusion of He et al. (2024), and ACP reduces improper governmental operations by restraining corrupt behaviors and enhancing market transparency, At the same time, ACP will also weaken companies' political ties and promote their shift toward green technological innovation, thereby reducing environmental problems such as CE(Chen et al., 2022). Therefore, ACP can alleviate the CE problem in general, confirming hypothesis H1.

Regarding the control variables, in column (2), the regression coefficient of EU was significantly positive at the 1% level. This indicates that high energy use increased CE. The World Energy Yearbook 2023 published by KPMG (2023) shows that the total global energy consumption reached 1.631 billion tons of oil equivalent in 2022, of which the three major fossil energy sources (oil, natural gas and coal) accounted for 82.6% of the share. This indicates that global energy use still relied on fossil energy sources, and high energy consumption led to high CE. The regression coefficient of GDP in column (3) was significantly negative at the 1% level. This may be because many countries, especially developed countries, have made efforts to manage the CE problem and realize the decoupling of CE and economic growth in the recent decade or so (Zhao et al., 2022). The regression coefficient of OP in column (4) was positive but did not pass the significance test. This may be due to the wide spatial scope of the sample selected in this paper. According to the different situations in different countries, different environmental regulations were implemented. Different types of foreign investment were treated in different way. In addition, the impact of foreign investment on CE varied. There existed a “pollution halo effect” and a “pollution tax haven effect” between them. CE also impacted international investment in reverse. They exhibited a two-way influence, which was insignificant (Pao et al., 2011). The regression coefficient of UR in column (5) was significantly positive at the 1% level because urbanization promoted CE by exacerbating energy demand through changes in industrial structure and increased social activities (Muhammad et al., 2024).

Table 2. Benchmark regression table

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
	CO_2	CO_2	CO_2	CO_2	CO_2
ACP	-0.0860*	-0.105**	-0.0863*	-0.0896*	-0.100**
	(-1.87)	(-2.29)	(-1.89)	(-1.96)	(-2.20)
EU		0.0128***	0.0176***	0.0176***	0.0152***
		(3.90)	(5.07)	(5.09)	(4.33)
GDP			-0.0757***	-0.0756***	-0.0733***
			(-4.07)	(-4.07)	(-3.96)
OP				0.0116	0.0109
				(1.14)	(1.08)
UR					0.522***
					(3.44)
Constant term	0.280***	0.251***	0.886***	0.885***	0.560***
	(13.67)	(11.64)	(5.64)	(5.64)	(3.07)
Country fixed	Y Y	Y	Y	Y	Y
Year fixed	Y	Y	Y	Y	Y
N	1089	1089	1089	1089	1089
R2	0.960	0.961	0.962	0.962	0.962
adj. R2	0.955	0.956	0.956	0.956	0.957

Note: Robust standard errors are shown in parentheses for each variable; ***, ** and * denote significance levels at 1%, 5% and 10%, respectively; The numbers in parentheses represent the t-test or Z-test values of the variables.

6. Robustness analysis

In this paper, three methods were used for robustness analysis. The first method replaced the explanatory variable (carbon intensity) in the baseline estimation with CE per capita (CC). The second approach to address the issue of sample selection bias is known as Song et al. (2023)'s method. And used instrumental variables to perform two-stage least squares regression (2SLS) with one-period lagged ACP degree (*L.ACP*) as an instrumental variable. The third method also used the instrumental variable method to perform 2SLS with the country's official language (*LAU*) as an instrumental variable in order to overcome the effect of endogenous variable problem. Column (1) in Table 3 shows that the regression coefficient of *ACP* was significantly negative at the 10% level after replacing the explanatory variable (carbon intensity) with CC. This indicates that the baseline regression results were robust.

Columns (2) and (3) in Table 3 show the results of the second robustness analysis using 2SLS. Referring to Ma et al. (2023) and Zheng et al. (2023), to address potential endogeneity in the control variables and to confirm the robustness of ACP and CE, L.ACP was utilized as an instrumental variable. Column (2) shows that the regression coefficient of *L.ACP* was significantly negative at the 1% level. This indicates that the degree of ACP in the previous period was significantly positively correlated with that in the current period. Column (3) shows that the correlation coefficient of *ACP* was still significantly negative at the 1% level. This is generally consistent with the baseline estimation, passing the robustness test.

Columns (4) and (5) in Table 3 demonstrate the results of the third robustness analysis using 2SLS. To overcome endogeneity, this paper used *LAU* as an instrumental variable (1 for English and 0 for non-English) in 2SLS to test robustness. Chen et al. (2013) found that the category of a country's official language significantly affected the economic behavior and perceptual habits of its nationals. Therefore, the official language in turn influenced various government policies and the behavior of political decision-makers, which satisfies the correlation requirement. The official language did not affect the level of CE, which satisfies the homogeneity requirement. The result in column (4) shows that the regression coefficient of *LAU* was significantly positive at the 1% level. This means that English-speaking countries had a higher degree of ACP. The regression coefficient of *ACP* in column (5) was significantly negative at the 1% level, meeting the baseline estimation and passing the robustness test.

Table 3. Robustness test table

Variable	CC（per capita carbon dioxide emissions）	L. ACP		LAU(language)	
	(1)CC	(2)ACP	(3)CO_2	(4)ACP	(5)CO_2
ACP	-1.379*		-0.206***		-0.297*
	(0.845)		(-2.931)		(-1.711)
L.ACP		0.628***			
		(23.466)			
GDP	0.428	0.004	-0.074***	0.042***	-0.039*
	(0.347)	(0.313)	(-3.898)	(3.143)	(-1.932)
OP	-0.073	0.005	0.012	0.000	0.000
	(0.188)	(0.928)	(1.292)	(1.449)	(1.259)
EU	0.958***	0.004*	0.018***		
	(0.065)	(1.766)	(5.176)		
UR	7.517***	0.038	0.350**	0.229*	0.547***
	(2.813)	(0.391)	(2.160)	(1.915)	(3.262)
LAU				0.625***	
				(7.780)	
Country fixed	Y	Y	Y	Y	Y
Year fixed	Y	Y	Y	Y	Y
Constant term	-3.724				
	(3.943)				
R^2	0.992				0.028

Note: Robust standard errors are shown in parentheses for each variable; ***, ** and * denote significance levels at 1%, 5% and 10%, respectively; The numbers in parentheses represent the t-test or Z-test values of the variables.

7. Further analysis

7.1 Analysis of intermediary effects

In order to verify whether ACP reduces CE by promoting the DE, this paper analyzed the channel effect of the

DE in terms of telecommunication infrastructure construction (TII), e-participation (EPI), and the level of Internet development (IU) (Table 4). In terms of telecommunication infrastructure, column (1) shows that the regression coefficient of *ACP* was positive but failed the significance test. As the fact that the telecommunication infrastructure in most countries is less affected and is mostly built by the telecommunication giants in their respective regions, such as China Mobile Communications Group Co., Ltd, AT&T, Deutsche Telekom. These firms are large and powerful and do not rely on government support through corrupt practices such as bribery for profitability. Therefore, they are less affected by corruption. Column (2) shows that the regression coefficient of TII was significantly positive at the 5% level. This may be because the consumption of equipment by some telecommunication giants worldwide has already had some positive effects on CE (Salahuddin et al., 2015). In terms of e-participation, in column (3), it is evident that the regression coefficient for ACP was notably positive at the 1% significance level. This implies that ACP could be addressed by building digital channels for citizen-government communication to enhance digital participation. Column (4) shows that the regression coefficient of EPI was significantly negative at the 10% level. This indicate that increased e-participation reduced CE because citizens can increase the level of government behavior regulation and environmental monitoring through online exposure-based supervision, thus reducing CE (Paunov, 2016). In terms of Internet share, Column (5) reports a positive and statistically significant coefficient for ACP, with significance at the 1% level. This suggests that ACP contributed to the country's Internet development, which corroborates the conclusion of Park et al. (2021). Park et al. argued that institutional pressure under ACP could be an important driver of enterprise digitization. Column (6) shows that the regression coefficient of IU was significantly negative at the 1% level. This counteracted the significance of the negative effect of the overall Internet development level on CE. This implies that the Internet was effective in reducing CE, supporting the conclusion of Zuo et al. (2024).

Although the impact of the digital economy on carbon emissions is positive in the TII channel, the impact direction remains negative in the EPI and IU channels. This overall directionality indicates that ACP indeed reduced CE by promoting the development of the DE. This effect was most significant in terms of e-participation and the Internet. Therefore, this paper concludes that ACP will reduce CE by promoting the development of the DE, especially in terms of e-participation and the Internet. Because ACP, as an important non-market strategy, helps companies concentrate resources, focus on innovation, and effectively respond to institutional pressures, thereby improving DE levels (Park et al., 2021). verifying hypothesis H2.

Table 4. Table for analysis of intermediation effects

Variable	Tii		Epi		IU	
	CO_2	CO_2	CO_2	CO_2	CO_2	CO_2
	(1)	(2)	(1)	(2)	(1)	(2)
	Tii	CO_2	Epi	CO_2	Iu	CO_2
ACP	0.0326	-0.166***	0.545***	-0.148**	15.83***	-0.0586
	(0.44)	(-3.31)	(3.00)	(-2.41)	(5.67)	(-1.28)
OP	-0.0211	0.0136	-0.001***	0.000	-0.324	0.009
	(-1.35)	(1.29)	(-3.27)	(0.65)	(-0.53)	(0.86)
EU	-0.012*	0.016***	0.0229	0.0144***	-0.456**	0.0130***
	(-1.86)	(3.75)	(1.60)	(3.01)	(-2.14)	(3.76)
UR	0.778***	0.434**	0.591	0.664***	-1.179	0.548***
	(3.12)	(2.58)	(0.85)	(2.86)	(-0.13)	(3.68)
TII		0.050**				

		(2.13)				
EPI				-0.026*		
				(-1.82)		
IU						-0.004***
						(-7.25)
Country fixed	Y	Y	Y	Y	Y	Y
Year fixed	Y	Y	Y	Y	Y	Y
Constant term	-0.749**	0.716***	-0.111	-0.138	-54.99***	0.341*
	(-2.46)	(3.49)	(-0.25)	(-0.93)	(-4.87)	(1.84)
N	936	936	664	664	1059	1059
R^2	0.965	0.950	0.850	0.952	0.981	0.964
adj. R^2	0.960	0.942	0.823	0.944	0.978	0.959

Note: Robust standard errors are shown in parentheses for each variable; ***, ** and * denote significance levels at 1%, 5% and 10%, respectively; The numbers in parentheses represent the t-test or Z-test values of the variables.

7.2 Threshold effect analysis

In order to explore the threshold effect of the DE during CE reduction by ACP, this paper examined the threshold effect from four aspects of the DE, namely, telecommunication infrastructure development (TII), e-participation (EPI), Internet (IU) and DE synthesis (DES). Table 5 shows that there was a double threshold effect in all four indicators.

Table 5. Threshold effect test table

Variable	Number of threshold	Threshold value	F value	P value	Critical value		
					10%	5%	1%
TII	Single threshold	0.21	48.51	0.01	25.974	29.3163	42.4077
	Double threshold	0.54	27.74	0.06	24.4538	29.1822	37.2227
EPI	Single threshold	0.33	50.51	0.01	23.6597	30.5714	48.3359
	Double threshold	0.65	26.67	0.07	22.3523	27.2396	40.6744
IU	Single threshold	40.12	46.44	0.02	27.0096	33.6321	52.0692
	Double threshold	67.25	26.67	0.08	25.485	31.2596	38.5305
DES	Single threshold	0.66	48.51	0.01	26.1113	31.9679	51.6226
	Double threshold	0.56	26.67	0.08	25.1962	31.0429	44.4191

Table 6 presents the regression results for the threshold effects of each variable under the different channels and summarizes the threshold effects of the DE. As demonstrated in the robustness checks – spanning multiple identification strategies – the control variables' coefficients exhibited remarkable stability, replicating the baseline findings without exception. Under the threshold of telecommunication infrastructure (TII), the relationship between ACP and CE varied with the TII level. When the degree of infrastructure development was low (TII ≤ 0.21), the negative effect of *ACP* on CO_2 was small and insignificant. The impact degree of ACP became gradually larger and more significant as TII increased. The regression coefficient was deepened from -0.065 to -0.183, passing the significance test at the 1% level. This means that the infrastructure development of the DE facilitated strengthening the mitigation effect of ACP on CE. The contribution of government and multinational enterprises to the DE, like digital backbone construction investments, promoted the development of the DE and enhanced social transparency using online monitoring or e-government. This thus significantly impacted their ACP processes (Lee et al., 2024). Higher broadband coverage and download speeds significantly increased the efficiency of public services, which in turn increased the income levels and willingness of citizens to pay taxes. This thus provided the government with sufficient funds and increased the level of public regulation of public services (Doran et al., 2022).

Regarding the threshold of e-participation (EPI), at a level of e-participation (EPI ≤ 0.33), the effect of ACP was small, and the regression coefficient passed the significance test only at the 10% level. As EPI rose, the effect of ACP became significant and deepened. The regression coefficient ranged from -0.060 to -0.179, passing the significance test at the 1% level. This also implies that increased participation in the DE was conducive to strengthening the mitigating effect of ACP on CE. This is because increasing the use of digital technologies in public services can improve the efficiency of public services. For example, empowering the healthcare system with digital technologies can massively reduce the cost of healthcare transactions for citizens, which increases their access to information (Sebastian et al., 2023).

Under the threshold of Internet usage (IU), the relationship between ACP and CO_2 was similar to that of the first two thresholds. The regression coefficient of *ACP* deepened from -0.053 to -0.187 as IU rose, passing the significance test at the 1% level. This again implies that the scale application of the DE enhanced the role of ACP on CE. The wide application of the Internet has spawned the extensive application of new modes of political governance such as e-government. This reduced human intervention within the government and facilitated the supervision of the behavior of government staff, improving the transparency of government external work (Li et al., 2021). In addition, a securely protected Internet prevented government data from private tampering, facilitating the eradication of ACP (Ibrahimy et al., 2020).

Similar to the first three thresholds, the regression coefficient of *ACP* deepened from -0.073 to -0.176 as DES increased, passing the significance test at the 1% level. This validated the findings of Shim et al. (2008).

It was also found that the change in significance was greater for countries that advanced from a low to a medium level of DE development than those from a medium to a high level. This implies that there may be a law of diminishing marginal utility in the impact of DE development on ACP, i.e., DE development had a more pronounced effect on countries with lower levels of DE.

To summarize, All four channels can create a more favorable environment for ACP to promote CE reduction to a similar extent and enhance the reduction effect of ACP. At the same time, EPI and IU can significantly produce this effect even at low levels. This is because DE technologies (such as anti-corruption platforms or blockchain technology) can enhance transparency and accountability mechanisms across government and the corporate sector, which is extremely effective in combating minor corruption. Therefore, DE has become an important measure to promote ACP and reduce CE. The above results confirmed hypothesis H3.

table 6. Threshold effect analysis table

Variable	TII		EPI		IU		DES
	CO_2		CO_2		CO_2		CO_2
GDP	-0.064*** (-2.85)	*GDP*	-0.064*** (-2.86)	*GDP*	-0.064*** (-2.86)	*GDP*	-0.064*** (-2.85)
OP	0.007 (0.72)	*op*	0.007 (0.73)	*op*	0.007 (0.72)	*op*	0.007 (0.73)
EU	0.016*** (4.69)	*EU*	0.016*** (4.70)	*EU*	0.015*** (4.69)	*EU*	0.0156*** (4.70)
UR	0.189* (1.91)	*UR*	0.188* (1.90)	*UR*	0.190* (1.91)	*UR*	0.186* (1.89)
ACP (*TII*≤0.21)	-0.065 (-1.56)	*ACP* (*EPI*≤0.33)	-0.060* (-1.65)	*ACP* (*IU*≤40.12)	-0.053* (-1.41)	*ACP* (*DES*≤0.56)	-0.073 (-1.62)
ACP (0.22-0.54)	-0.135*** (-2.91)	*ACP* (0.34-0.65)	-0.127*** (-2.95)	*ACP* (40.13-67.25)	-0.130*** (-3.01)	*ACP* (0.56-0.66)	-0.128*** (-2.89)
ACP (*TII*>0.54)	-0.183*** (-4.53)	*ACP* (*EPI*>0.65)	-0.179*** (-4.71)	*ACP* (*IU*>67.25)	-0.187*** (-4.62)	*ACP* (*DES*>0.66)	-0.176*** (-3.90)
Constant term	0583*** (-5.08)	Constant term	0.701*** (-6.13)	Constant term	0.651*** (-5.06)	Constant term	0.690*** (-5.13)
Country fixed	Y		Y		Y		Y
Year fixed	Y		Y		Y		Y
N	1089	N	1089	N	1089	N	1089
R2	0.125	R2	0.126	R2	0.125	R2	0.125
adj. R2	0.011	adj. R2	0.010	adj. R2	0.011	adj. R2	0.009

Note: Robust standard errors are shown in parentheses for each variable; ***, ** and * denote significance levels at 1%, 5% and 10%, respectively; The numbers in parentheses represent the t-test or Z-test values of the variables.

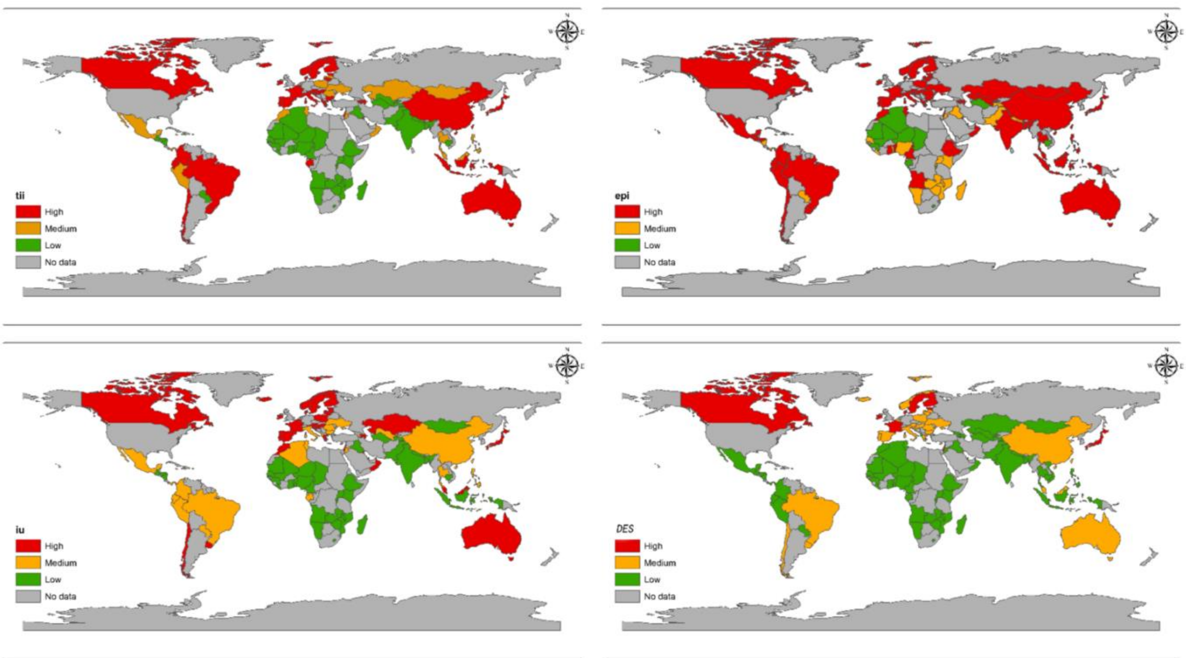

Figure 2. Differences in the degree of development of TII, EPI, IU, DES among countries according to thresholds

Color Legend: Green = Low, Yellow = Medium, Red = High. Thresholds: TII (0.21, 0.54), EPI (0.33, 0.65), IU (40.12, 67.25), DES (0.56, 0.66).

Data source:World Bank,UN Trade and Development(UNCTAD).

Based on the two thresholds of each indicator, this paper categorized countries below the first threshold for each of the four indicators as low (green), those between the two thresholds as medium (yellow) and those above the second threshold as high (red), and projected them on a world map (Figure 2). The level of DE development showed significant continental differences across countries. Nations with advanced DE, such as Canada, Denmark, Finland and France, were mostly concentrated in Europe and the Americas. Countries with a medium to low development level, such as Jamaica, Burundi, Mauritania, India and Indonesia, were mostly located in Asia and Africa. This may be because the time frame and intensity of the digital technology revolution varied across continents with different levels of economic development.

8. Heterogeneity analysis

This paper analyzed heterogeneity at the level of continents and colonial history. At the continental level, it is also clear from the threshold effect analysis above that the development of the DE varied across continents. Therefore, the influence of the DE on economic development and political conditions varied, leading to differences in the impact of ACP at the continental scale. For example, the marginal impact of DE development on ACP may be greater in regions with greater potential for economic development, such as East Asia or South America (Thomas, 2009)(Satish et al., 2013). Meanwhile, most of the current studies have been centered on local regions. This study selected the global panel data of 121 countries over a nine-year period. A wider scope facilitated the heterogeneity analysis of the relationship between ACP and CE at the continental level. At the level of colonial history, colonial history may be a hidden factor influencing corruption and the DE. With respect to corruption, Dealy (2003) argued that colonial history could bring some hierarchical concepts to a colony, such as ideas of inequality and centralism. These concepts could exacerbate the level of corruption in a country, making ACP more challenging as the colony became increasingly influenced by the sovereign state. Acemoglu et al. (2003) also supported the conclusion that colonial governments usually have more power and more secretive factional mechanisms than ordinary governments, which can seriously affect the economic development of the colonies. For example, the colonial government would force the locals to engage in a single economic activity and prevent industrial structure upgrading, severely limiting the development of local science and technology. Lagging technological development can also adversely affect a country's current digital economic development. Meanwhile, the robustness analysis in the previous section also concluded that there were differences in the level of ACP between English-speaking and non-English-speaking countries, and many English-speaking countries had a history of being colonized (Zeng et al., 2024). This provides a basis for speculating on the impact of colonial history on corruption. For digital economic development, Kwet (2019) noted that during the colonial period, industrialized powers such as the United States and the United Kingdom systematically enforced policies rooted in colonial domination and racial segregation, as evidenced by their historical actions toward territories like the Philippines and South Africa. In the 21st century, with the development of digital technology, they have used their digital technology advantages and their original colonial advantages in the colonized countries to digitize their colonial acts, influencing a country's labor force, economy and even education. For example, they can monitor the Internet behavior of nationals of colonized countries or control market capital through digital technology (Pinto R.Á, 2018). This suggests that traditional colonization provides a basis for modern digital colonization, and therefore the colonial context may influence the DE development of a country. In summary, the colonial context may influence a country's political landscape (such as corruption) and its modern DE development, thus impacting the role of its DE on ACP and CE.

Table 7 shows that, in terms of continental heterogeneity, the relationship between ACP and CE varied across countries on different continents. The regression coefficients of *ACP* were significantly negative at the 1% level for African and European countries and insignificantly negative for Asian and Oceanian countries. This is related to the overall CE situation of the continents. The level of CE was generally low in African and European countries and high in Asian and Oceania countries. ACP and CE in countries with higher CE exhibited a more complex nonlinear relationship. Thus, the linear correlation was insignificant, which was supported by the results of Zhang et al. (2016). Meanwhile, the regression coefficient of *ACP* in American countries was significantly positive at the 10% level. This phenomenon can be elucidated through the lens of economic development. Corruption can reduce the increasing effect of the economy on CE by decreasing economic income in the front part of the EKC curve, thus reducing CE (Matthew, 2007). Therefore, ACP and CE may show a positive correlation. Regarding colonial heterogeneity, the regression coefficient of *ACP* was insignificantly positive for countries with colonial history and significantly negative at the 5% level for countries as non-former colonies. This supported the EKC theory (Grossman, 1992) and the speculation in the previous section that colonial history had a negative impact on a country's economic and digital development in the DE. If a country was colonized, then its political governance and digital economic development would have been influenced by its colonial history to some extent. This would lead the economic situation of the country to be at the front of the EKC. Corruption can reduce CE by hindering economic development, and therefore ACP can promote CE. In addition, DE development may have been disturbed by the former suzerain state with a low degree of development, which cannot well enhance the effect of ACP on CE reduction. However, if a country was not a former colony, its economic development would tend to be smoother and may even have been boosted by plundering more resources through previous active colonization. Most of these countries would be at the back of the EKC and have a higher degree of DE development, thus facilitating ACP effects on reducing CE. These findings reveal that although ACP has an overall negative impact on CE at the global level, economic development level and colonial history can reverse the relationship between ACP and CE through impediments to income and DE development in some continents and countries with colonial history.

Table 7. Heterogeneity analysis table

Variables	Continental heterogeneity					Colonial heterogeneity	
	Africa	America	Asia	Europe	Pacific	former colony	Non-former colonial
ACP	-0.181***	0.084*	-0.141	-0.237***	-0.138	0.080	-0.114**
	(0.064)	(0.050)	(0.117)	(0.070)	(0.136)	(0.063)	(0.053)
GDP	0.027	-0.027	-0.024	-0.214***	0.496	-0.090***	-0.062***
	(0.025)	(0.029)	(0.048)	(0.038)	(0.401)	(0.030)	(0.021)
Op	0.023	-0.039	0.570***	-0.007	0.230	0.001	0.015
	(0.032)	(0.060)	(0.082)	(0.008)	(0.352)	(0.015)	(0.012)
EU	0.166***	0.013***	0.006	0.033***	-0.005	0.025***	0.014***
	(0.029)	(0.003)	(0.007)	(0.006)	(0.011)	(0.009)	(0.004)
UR	1.029***	0.016	-0.360	0.957***	14.486	-0.708***	0.928***
	(0.207)	(0.164)	(0.366)	(0.320)	(7.533)	(0.184)	(0.185)
Constant term	-0.385	0.279	0.523	3.028***	-19.386	1.436***	0.205
	(0.248)	(0.311)	(0.466)	(0.558)	(10.517)	(0.331)	(0.246)
Country fixed	Y	Y	Y	Y	Y	Y	Y
Year fixed	Y	Y	Y	Y	Y	Y	Y
N	315	189	297	261	18	180	909

R^2	0.972	0.996	0.953	0.963	1.000	0.978	0.962

Note: Robust standard errors are shown in parentheses for each variable; ***, ** and * denote significance levels at 1%, 5% and 10%, respectively; The numbers in parentheses represent the t-test or Z-test values of the variables.

9. Main Conclusions and Prospects

9.1 Conclusions

Leveraging a global panel dataset encompassing 121 countries (2013-2021), this study employs a multistep econometric approach — integrating incremental regression analysis with a nonlinear threshold regression framework — to systematically examine both the aggregate effect of ACP on CE and the critical moderating role of DE development in ACP-driven CE mitigation. From the empirical findings, the following conclusions have been derived: (1) ACP mitigates the CE problem, passing a series of robustness tests. (2) Mediating effect analysis shows that ACP reduces CE by promoting DE development, and this effect is most obvious in the channels of e-participation and the Internet. (3) Threshold effect analysis shows that telecommunication infrastructure construction, e-participation, the Internet and DE synthesis all have a threshold effect on CE reduction by ACP. This indicates that the DE is an important factor in boosting ACP to reduce CE. Higher levels of the DE will strengthen the role of ACP in reducing CE. (4) Heterogeneity analysis shows that the relationship between ACP and CE varies across continents due to varying overall CE and economic development. Some continents with higher CE have a DE that makes a greater marginal contribution to ACP. Thus, the linear relationship between ACP and CE is more significant. Some continents with weaker economic development tend to be in the front part of the EKC. Thus, the impact of ACP on CE is positive. Meanwhile, the study also analyzes a new heterogeneous entry point, namely, colonial history. Colonial history can have substantial adverse effects on the present-day politics and economy of a country, leading to the country being in the front of the EKC. Therefore, the degree of ACP in former colonized countries tends to have a positive effect on CE, whereas the opposite is true for non-former colonized countries.

This paper investigates some roles of the DE in the relationship between ACP and CE through a series of empirical analyses. The findings contribute to advancing current related research, but there are still many limitations. Firstly, the problem of time span. Limited by data availability, this paper only covers a nine-year period and fails to fully explore the relevant issues in the long-term situation. Secondly, this paper only relies on the International Corruption Perceptions Index (CPI) for ACP-related research. CPI relies mainly on the evaluation of experts and businessmen in various countries and may lack some objectivity. In addition, as this study covers panels worldwide, the results may not be universally applicable to all countries and regions, and may not be as detailed as articles that focus on a specific country or certain countries and regions, which are of particular interest to the academic community. In the future, for such a global macro topic, it is necessary to draw more generalized conclusions based on a long period. More diversified research indicators need to be developed to ensure the objectivity of the research, at the same time, more diverse models should be incorporated to comprehensively analyze other impact mechanisms of the digital economy (such as spillover effects).

9.2 Policy recommendations

In light of the aforementioned findings, the following policy recommendations are proposed: (1) Political factors have a significant impact on pollution and carbon reduction effectiveness. Corruption exacerbates environmental problems at the level of the rule of law and impacts industry and cultural education. Actively fighting against corruption is important and necessary to mitigate the CE problem. Thus, countries should actively take measures to maintain political governance quality, such as improving the rule of law, strengthening the monitoring mechanism, implementing ACP education and cultural activities and participating in the development of international ACP cooperation, in order to fight against corruption. (2) The strategic integration of digital economy (DE) advancements serves as a critical anti-corruption mechanism to accelerate carbon emission (CE) mitigation. E-governance platforms and internet-based transparency tools can disrupt rent-seeking networks by enhancing public accountability and institutional oversight. Policymakers must therefore institutionalize synergies between anti-corruption policies (ACP) and DE infrastructure, Utilizing blockchain verification and AI-driven audit systems to achieve full traceability of government funds and preemptively curb corruption in environmental governance. (3) The DE can create an environment more conducive to CE reduction and strengthen the effect of ACP in reducing CE. Countries should actively promote DE development, construction of DE, popularization of the Internet and extensive application of digital technologies. For countries with low DE levels, strengthening e-government and internet infrastructure can better achieve the ACP's role in curbing CE. For countries with high DE levels, however, it is necessary to strengthen the deep integration of DE, ACP, and carbon emission reduction, such as promoting anti-corruption technological innovations like blockchain and artificial intelligence environmental monitoring. At the international level, a joint digital-climate working group should be established under the COP framework to develop cross-border carbon data blockchain standards. At the same time, the carbon footprint of corruption should be incorporated into the UNEP System of Environmental-Economic Accounting (SEEA), ultimately forming a virtuous cycle where anti-corruption drives the digital economy and the digital economy empowers carbon reduction. (4) Countries should emphasize the CE issue, actively promote pollution prevention and control and carbon emission reduction, extensively participate in international cooperation on carbon emission reduction, and strive to achieve carbon peaking and carbon neutrality while maintaining economic development. In addition, countries should also promote the sound construction of their political environments and pay attention to the interference and negative influence of some developed countries and Internet powers on their political governance in the digital era.

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Conflict of Interest

The authors declare no conflict of interest.

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