6. Computing Ripples: How AI Computing Power Drives the Sustainable ESG Progress of Chinese Corporations[1]

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Abstract

This paper explores the long-term ripple effects of Artificial Intelligence Computing Power (AICP) on corporate Environmental, Social, and Governance (ESG) performance. Quantitative analysis reveals a complex interplay between China's AICP and corporate ESG performance. Moreover, the integration of AI computing power and ESG has generated widespread and profound "ripple effects" on global sustainable transformation and economic development. By delving into the dynamic interaction mechanisms between the two, this study unveils the mysteries behind these ripple effects. Finally, the findings offer meaningful policy recommendations for the synergistic development of digital intelligence and sustainability.

Keywords: *Artificial Intelligence Computing Power; corporate ESG; sustainable development; time-varying interactions; China.*

JEL Classification: *C32, Q56, O33, M14.*

1. Introduction

This paper aims to explore the complex interrelationship between artificial intelligence computing power and corporate ESG (Environmental, Social, and Governance) performance. In recent years, climate change, social inequality, and corporate governance issues have increasingly become global focal points, driving the widespread adoption of the ESG framework (Escrig-

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Olmedo et al., 2019; Qin et al., 2024). ESG servers as a key tool for measuring the non-financial performance of listed companies and guides businesses in integrating environmental, social, and governance considerations into their business models (Li et al., 2024). However, with the growing global demand for sustainable development, accurately assessing and improving ESG performance remains a challenge (Clément et al., 2022). Traditional ESG assessments rely on manual data collection, which suffers from inefficiency, data inconsistencies, and vague evaluation standards (Avramov et al., 2022; Liu et al., 2024). These issues make it difficult for companies to accurately measure and forecast long-term risks and opportunities, thus lowering ESG performance (Berg et al., 2022). AI, with its powerful computing capabilities, enables efficient data analysis, predictive simulations, and automated reporting, helping to establish more consistent and transparent ESG standards (Zhang & Zhang, 2024). AI computing power also assists companies in optimizing resource allocation, thereby enhancing ESG performance (Khoruzhy et al., 2022; Qin et al., 2024a). For example, Alibaba has utilized AI computing power to optimize logistics and warehousing, significantly reducing carbon emissions during transportation and improving the company's environmental ESG performance (Zhang & Ravishankar, 2019). Additionally, the integration of AI computing power with ESG has strengthened economic forecasting capabilities, helping companies to identify complex environmental and social risks earlier, enabling them to make innovative decisions in dynamic markets. Therefore, AI computing power not only improves the accuracy of ESG assessments but has also become a core engine driving low-carbon transformation, creating a significant "ripple effect" on global sustainable change and economic development. This "ripple effect" refers to the widespread, long-term consequences that extend beyond the immediate impacts on individual companies. As AI technologies optimize resource allocation, reduce emissions, and enhance operational efficiency, their positive outcomes reverberate throughout industries, influencing related sectors and even encouraging the adoption of sustainable practices across regions and economies. These cascading effects amplify the overall sustainability agenda, fostering greater systemic alignment between AI, clean energy, and global economic development. This paper, by exploring the ripple effects of AI computing power on corporate ESG performance, aims to provide comprehensive insights for companies and policymakers to assess and improve ESG governance, thereby assisting companies in achieving long-term alignment between economic growth and sustainable development goals.

In recent years, China has achieved a leading position in the global AI computing power field and has played a significant role in promoting sustainable development and improving ESG performance (Wu et al., 2020; Qin et al., 2024). Therefore, It is crucial to delve deeper into the distinctive aspects of China's AI and ESG. China's rapidly growing AI industry is uniquely positioned due to strong government support through initiatives such as the New Generation Artificial Intelligence Development Plan, which aims to establish China as a global leader in AI by 2030. These government-backed programs provide substantial funding and regulatory frameworks in AI's applications (Su et al., 2024). In contrast, developed nations like the U.S. and EU rely more heavily on private sector innovation and market competition to drive AI development, resulting in a more decentralized AI ecosystem (Alfalih, 2023). Similarly, China's ESG practices are deeply shaped by policy-driven sustainability goals and the dominance of state-owned enterprises (SOEs). For example, Chinese ESG initiatives are often aligned with national objectives, such as carbon neutrality by 2060 and the "dual carbon" goals outlined in the 14th Five-Year Plan (Dadao, 2019; Cao et al., 2024). This alignment ensures that ESG practices are integrated into corporate strategies of SOEs, which play a critical role in sectors such as energy, infrastructure, and manufacturing. With strong policy support, China's AI computing power has been widely applied (Yang & Huang, 2022). By 2023, the AI computing power market size had exceeded 400 billion yuan, becoming an essential part of the global AI market. Additionally, the Chinese government has recognized the ripple effect of AI computing power in enhancing corporate ESG performance and actively promoted projects like the "East Data, West Computing" initiative and the "Green Belt and Road" project. These projects reduce carbon emissions through intelligent solutions and improve corporate resource management transparency, promoting regional economic coordination and sustainable development (Zhang et al., 2024). In comparison, this centralized approach differs from the fragmented regulatory environments in the U.S. and EU, where diverse stakeholders and regional policies often delay ESG implementation (Burnaev et al., 2023). Therefore, by analyzing these distinctions, we recognize that China provides a compelling case and China's AI computing power is closely related to corporate ESG performance. However, there has been no systematic research on this issue to date. This study will fill these gaps.

The marginal contributions of this paper are as follows: First, most previous research has treated technology as a static and singular variable, but they overlook the complex and far-reaching effects that technological advancements evolve over time. Therefore, we decided to explore the long-term dynamic impact of the two. Through experiments, we revealed that AI computing power not only helps companies improve ESG performance but also generates ripple effects on a broader scale over time. Second, We chose the China Securities ESG 300 Index (ESG), which includes 300 representative companies, to provide a more comprehensive and accurate description of corporate ESG performance. Additionally, this paper selected the AI Computing Power Concept Index (AICP) from the Wind database to represent advancements in AI computing power. This not only enriches the theoretical foundation of AI computing power's impact on ESG performance but also offers new avenues for future research in related fields. Finally, this paper applies a novel sub-sampling technique to track the time-varying transmission mechanism between AICP and ESG. The relationship between AICP and ESG evolves over time, and traditional full-sample tests are prone to errors due to time-varying parameters. Therefore, this paper employs a modified LR causality test with RB bootstrap to address this issue, revealing the long-term relationship between AICP and ESG. The results show that while AI computing power promotes corporate ESG performance, the energy consumption and governance instability brought about by AI computing power centers cannot be ignored. Moreover, the pressing need for businesses to develop new business models and set environmental goals has further accelerated the progress of AI computing power.

2. Literature review

The impact of AICP on ESG performance has been widely discussed, but the academic community has not yet reached a consensus. Some scholars argue that AICP can help companies assess and improve ESG performance more accurately (Su et al., 2024). AI technology enables companies to intelligently manage carbon emissions and resource use, thus promoting the realization of low-carbon economy and social responsibility goals (Li et al., 2024). Additionally, AICP can significantly enhance the accuracy of ESG data analysis, predictive modeling, and decision-making processes, thereby helping companies assess and improve ESG performance (Su et al., 2024). However, another group of scholars points out that the rapid development of AICP is also accompanied by the risks of high energy consumption, social instability and data privacy exposure, which undoubtedly pose a challenge for companies to improve their ESG performance (Stahl & Wright, 2018; Burnaev et al., 2023).

AICP positively influences corporate ESG performance across multiple dimensions. From an environmental perspective, AICP-driven intelligent models facilitate technological innovation and encourage investment in emissions reduction, thereby supporting corporate pollution control efforts (Su et al., 2024; Lee et al., 2024). Additionally, AICP leverages machine learning (ML) to optimize resource management within supply chains, enhancing resource efficiency and contributing to sustainability objectives (Pappaterra, 2022). They also emphasize AI-driven green finance initiatives, where AICP supports sustainability-linked investments and carbon trading mechanisms, further promoting environmentally responsible corporate practices.From a social perspective: On one hand, AICP enhances employee training in AI applications, thereby improving their human capital (Su et al., 2024). On the other hand, AICP can use intelligent algorithms to detect inequalities in the labor market, helping companies develop fair compensation structures and diversity policies, which in turn improve ESG social performance (De Stefano; 2019). From a governance perspective, Hilb (2020) argues that AICP strengthens corporate oversight by enabling real-time data monitoring and predictive analytics, allowing boards and management to identify and mitigate potential risks. AI-driven regulatory compliance systems help companies navigate evolving ESG disclosure requirements by dynamically adapting to changes in policies and industry standards (Alfalih, 2023). As ESG reporting regulations become more stringent, AI-based compliance solutions are increasingly being integrated into corporate governance frameworks to ensure regulatory adherence and ethical risk management.

However, there are differing views in the academic community regarding whether AICP can enhance ESG performance. Some studies highlight that AI-driven computing requires substantial investment in infrastructure and energy resources, leading to heightened carbon emissions from large-scale GPU and server operations (Dayarathna et al., 2015; Su et al., 2024). Additionally, while AI enhances data analysis capabilities, it also introduces ethical and security risks. Concerns over data privacy breaches and regulatory non-compliance pose reputational and legal challenges for firms deploying AI at scale (Stahl & Wright, 2018; Su et al., 2024). The affordability and accessibility of AI computing power also play a critical role in determining ESG outcomes. High implementation costs may limit the widespread adoption of AI-driven ESG solutions, particularly among small and medium-sized enterprises (SMEs). Without adequate financial support, such as government subsidies or cost-sharing initiatives, many businesses may struggle to integrate AI into their ESG frameworks effectively. Moreover, inconsistencies in AI and ESG regulatory frameworks across industries hinder the seamless integration of AI computing power, limiting its broader scalability in corporate sustainability efforts (Qin et al., 2024).

Therefore, AICP plays a dual role in enhancing corporate ESG performance. By deeply identifying the time-dependent interactions between AICP and ESG, we reveal the sustained impact of AICP on ESG performance across different time dimensions, as well as the feedback mechanism of ESG indicators on AICP. AICP enhances corporate environmental management, resource optimization, and governance levels, while standardized ESG frameworks also drive the development of AI computing power. This synergistic effect supports sustainable development and strengthens the forward-looking nature of economic forecasts, enabling businesses and policymakers to more effectively address future environmental and social risks.

3. Methodology

3.1. Full sample technique

Generally, the Granger causality test can yield unbiased and consistent estimators. However, since the assumption of asymptotic normal distribution is often challenging to satisfy, Shukur and Mantalos (2004) proposed the Residual Bootstrap (RB) method as an effective solution to this issue. Additionally, with smaller sample sizes, the Monte Carlo Simulation (MCS) method may introduce some errors in improving the Wald test. In view of this, we employ the RB-adjusted LR test to explore the causal relationship between AICP and ESG. The specific form is shown in the following formula:

$$X_t = \beta_0 + \beta_1 X_{t-1} + \cdots \ldots + \beta_p X_{t-p} + \varepsilon_t, \ \ t = 1,2 \ldots \ldots T \tag{1}$$

Subsequently, we determine the optimal lag order according to the SIC criterion and denote X as $X_t = (\mathrm{AICP}_t + \mathrm{ESG}_{2t})'$, Then we obtain equation (2) :

$$\begin{bmatrix} AICP_t \\ ESG_{2t} \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} ALCP_t \\ ESG_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (2)$$

$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$ is a white noise process; $\beta_{ij}(L) = \sum_{k=1}^{p} \beta_{ij,k} L^k; i, j = 1,2$; L is a lag operator. We establish the original hypothesis that there is no causal relationship between AICP and ESG:$\beta_{12,K} = 0,\ k = 1,2,\ldots\ldots, p$. On the contrary, $\beta_{21,K} = 0,\ k = 1,2,\ldots\ldots, p$.

3.2. Stability test of parameters

We typically assume in full-sample causality tests that the parameters used in vector auto-regression models exhibit stable changes over time (Su et al., 2020). Considering that parameters in real-world scenarios may display non-stationary behavior, we refer to the studies by Andrews (1993) , applying the Sup-F test for structural change in the model and using the AVE-F and Exp-F tests to examine whether the model varies over time. Additionally, based on Nyblom (1989), we utilize the LC test to determine if there is a random walk process between variables. Since time-varying parameters may cause instability in the relationship between AICP and ESG, potentially introducing bias into the full-sample estimation results. We further employ a sub-sample technique to more accurately estimate the mutual relationship between them.

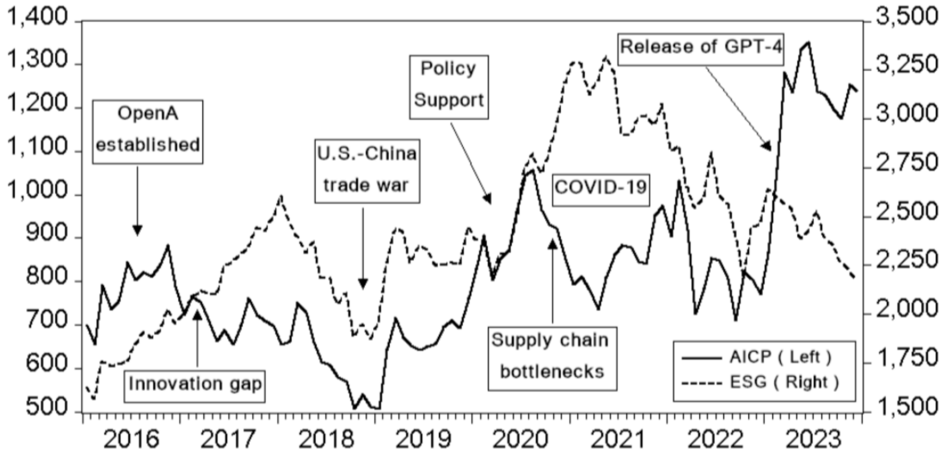
3.3. Sub sample technique

The rolling window test divides a time series into discrete intervals by setting a window width (Balcilar et al., 2010). However, determining an optimal window width is challenging, as both excessively large or small widths may lead to biased estimation results. Following the approach of Pesaran and Timmermann (2005), we assume a time series length of T and a window width w. Each segment spans from w、$w + 1, \ldots\ldots$, up to T, resulting in $T - w + 1$ time series segments. We then apply the RB-adjusted LR test within each sub-sample to examine their causality. Finally, we aggregate the LR statistics and p-values sequentially over time. $N_b^{-1} \sum_{k=1}^{p} \hat{\beta}_{21,k}^{*}$ and $N_b^{-1} \sum_{k=1}^{p} \hat{\beta}_{21,k}^{*}$ $N_b$represent the effects of AICP on ESG and ESG on AICP across all bootstrap estimations. $\hat{\beta}_{21,k}^{*}$ and $\hat{\beta}_{21,k}^{*}$ are the parameters from equation (2), and we set the confidence interval at 90%, with the upper and lower bounds at 5% and 95%.

4. Data

This paper utilizes monthly data from January 2016 to December 2023 to explore the interaction between the development of China's AI computing power and corporate ESG performance. The chosen period stems from 2016, known as the year AI began its commercial application in China (Roberts et al., 2021). During the "13th Five-Year Plan," China designated AI as a major project, providing policy support for its commercialization. By 2023, significant advancements in AI computing power were achieved. Breakthroughs in AI large language models, represented by ChatGPT, spurred a global surge in intelligent computing development (Rai, 2024; Su et al., 2024). Furthermore, as China shifts towards a high-quality, sustainable economic development model, the government increasingly requires corporations to prioritize environmental, social, and governance (ESG) issues (Meng et al., 2023). In June 2016, the government released the "Guiding Opinions on State-owned Enterprises Better Fulfilling Social Responsibilities," marking widespread attention to corporate social responsibility. By 2023, the International Sustainability Standards Board (ISSB) released its first set of global standards for sustainability disclosure, significantly enhancing the transparency, accountability, and efficiency of global sustainability information disclosure. In view of this, this paper chooses the A-share AI Computing Power Concept Index from the Wind database (code: 8841678.WI) to measure AI computing power development trends, and the CSI ESG300 Index (code: 399378.SZ) to represent corporate ESG performance in China. These indices were chosen for their comprehensiveness, reliability, and alignment with the key dimensions of AI development and ESG practices. The A-share AI Computing Power Concept Index reflects trends in the commercialization and technological advancements of AI computing power in China, providing a robust measure of AI's growth across industries. Similarly, the CSI ESG300 Index offers a comprehensive evaluation of corporate ESG performance, as it includes 300 representative companies across various sectors, making it a reliable indicator for analyzing ESG trends in the Chinese context. Compared to alternative measures, these indices provide unique insights. Both indices are positive indicators, meaning higher values signify better development or performance, which facilitates a clear and consistent analysis of trends and interactions between AI and ESG.

Figure 1. The trends of AICP and ESG



Source: own graph in EViews 12.

As shown in Figure 1, the trends in AICP and ESG development are not entirely aligned throughout the sample period. The full-sample analysis may not adequately capture their causal relationship. Therefore, we employ sub-sample testing to capture their connection more accurately.

Table 1. Descriptive statistics for AICP and EST

	AICP	ESG
Observations	96	96
Mean	822.072	2406.815
Median	790.946	2376.079
Maximum	1351.809	3318.856
Minimum	505.437	1564.164
Standard Deviation	189.421	403.181
Skewness	1.0171	0.3316
Kurtosis	3.7189	2.7069
Jarque-Bera	18.621***	7.103**
Probability	0.000	0.035

Source: own calculations in EViews 12; Notes: ***is the significance at a 1% level.

Table 1 presents the descriptive statistics for AICP and ESG. The Jarque-Bera test results show that the assumption of normal distribution for both AICP and ESG series is strongly rejected at least the 5% level. This implies that results derived from Granger causality testing within the VAR model framework may lack accuracy. To address this issue, we employ the RB-based revised-LR technique and use sub-sample analysis to explore the evolving transmission mechanism between AICP and ESG.

5. Quantitative Analyses and Discussions

After applying the first-order difference to AICP and ESG, we conducted ADF, PP, and DF-GLS tests to assess their stationarity. As shown in Table 2, the coefficients of AICP and ESG in each test are significant at the 1% level, indicating that both variables are stationary. Therefore, we constructed a bivariate VAR model to examine the Granger causality relationship between AICP and ESG across the full sample.

Table 2. The results of unit root tests

Variables	ADF	PP	DF-GLS
AICP	-9.216 (0)***	-9.223 [1]***	-7.375(0)***
ESG	-9.610 (0)***	-9.611 [3]***	-7.917(0)***

Source: own calculations in EViews 12.

We determined the optimal lag order as 2 based on the SIC value, using Bootstrap with 1000 repetitions. As shown in Table 3, the Granger causality test between AICP and ESG did not yield significant results, indicating that AICP does not impact ESG, nor does ESG impact AICP. This finding is inconsistent with existing studies

Table 3. The outcomes of bootstrap full-sample method

H0: AICP is not the Granger cause of ESG		H0: ESG is not the Granger cause of AICP	
Statistic	p-value	Statistic	p-value
4.009	0.200	5.523	0.110

Source: own calculations in EViews 12.

Table 4. The outcomes of parameter stability techniques

Tests	AICP		ESG		VAR (s) process	
	Statistics	p-values	Statistics	p-values	Statistics	p-values
Sup-F	39.108***	0.000	27.092***	0.001	19.032***	0.000
Ave-F	8.509***	0.000	8.346*	0.07	9.725*	0.054
Exp-F	15.344***	0.000	10.016***	0.001	7.127**	0.026
Lc					1.499**	0.031

Source: own calculations in R.

Further, we found that many studies analyze time series data based on the assumption that no structural change occurs due to a single causal relationship. However, in full-sample tests, structural shifts in VAR estimates can lead to changes in the relationships among parameters over time (Balcilar et al., 2010). This suggests that the Granger causality relationship between AICP and ESG may be unstable. To address this issue, we applied the following four tests to examine the stability of the two parameters and determine whether random walks may occur (Nyblom, 1989；Andrews, 1993). The results are presented in Table 4.

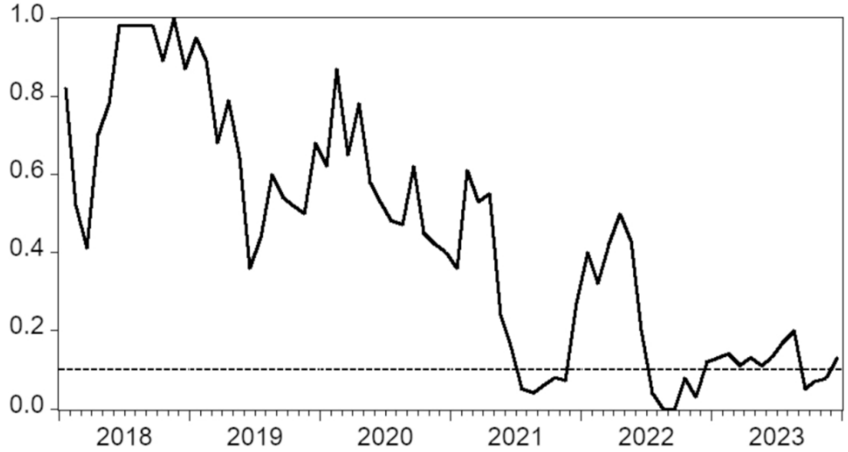
The test results indicate that the Sup-F, Ave-F, Exp-F, and VAR tests are all significant at least at the 10% level, and the Lc test is significant at the 1% level. This strongly rejects the null hypothesis, indicating that the parameters do not follow a random walk. These tests also confirm that a time-varying relationship exists between AICP and ESG, which would not be captured through constant causality assessment methods, making a full-sample test inappropriate. Therefore, we employed a rolling-window sub-sample approach to capture the dynamic relationship between AICP and ESG. To ensure accuracy, we set the rolling window width to 24 months, with an observation period from January 2016 to December 2023. The rolling test results are shown in Figures 2 through 5 below, illustrating whether the hypothesis that AICP is a Granger cause of ESG (or vice versa) can be rejected and indicating the specific direction of influence between the two variables.

Figure 2 and figure 3 show the direction of the p-value and the direction of the impact of AICP on ESG, respectively. Hence, it can be concluded that from June 2021 to November 2021, June 2022 to December 2022, and May 2023 to November 2023, the initial hypothesis—that AICP does not Granger-cause ESG—is rejected at the 10% significance level. Moreover, AICP exhibits a similar growth trend to ESG during June 2022 to December 2022 and May 2023 to November 2023. In contrast, AICP has a negative effect on ESG from June to November 2021. This highlights the existence of periods where AICP significantly influences ESG performance, with variations in both the strength and direction of the impact, driven by underlying dynamic mechanisms.

From June to November 2021, AICP exhibited an upward trend, while ESG experienced a decline. The negative impact of AICP on ESG during this period can be primarily attributed to the dual influence of policy direction and energy structure. During this time, the Chinese government formulated the "14th Five-Year Plan for the Development of the Information and Communications Industry," which emphasized the expansion of computing power in data centers. Driven by this policy, China's AICP experienced rapid growth. By the end of 2021, China's computing power had reached 140 EFlops (FP32), ranking second globally, with 36% of the capacity attributed to intelligent and supercomputing resources. However, as AICP increased, the construction of AI data centers also expanded, leading to a notable rise in traditional high-carbon energy consumption (Li et al., 2023). For instance, in response to the power shortages of 2021, manufacturing-intensive provinces such as Guangdong and Zhejiang resumed coal-fired power generation. This increased energy consumption, directly conflicting with carbon neutrality targets, which led to a decline in the ESG performance of corporations. Therefore, AICP's impact on ESG exhibited a negative relationship.

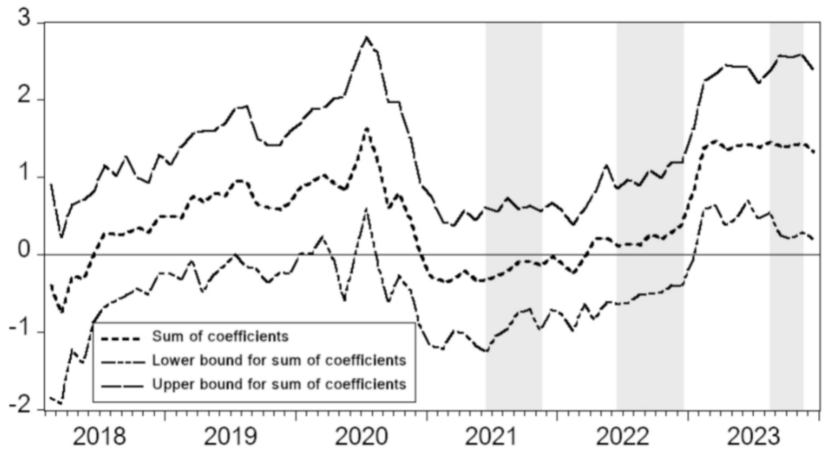
From June to December 2022, AICP had a positive impact on ESG, with both showing a rapid upward trend.This positive relationship was driven by technological advancements and regulatory measures that improved energy efficiency and reduced carbon emissions. Firstly, China continues to advance the "Eastern Data, Western Computing" project launched in 2022, optimizing the national computing power layout to reduce energy consumption and costs (Zhang et al., 2024). Companies leveraged advanced AICP for ESG management, including carbon emissions monitoring and supply chain optimization, which directly improved their environmental performance. What's more, the "Three-Year Action Plan for New Data Center Development (2021-2023)" issued by the Ministry of Industry and Information Technology played an important role during this period. This policy required the green and intelligent construction of new data centers, reducing dependency on fossil fuels and minimizing environmental impacts (Li et al., 2023). Therefore, major technology companies such as Baidu, Alibaba, and Tencent (BAT) increased their investments in green computing technologies. For example, they all adopted liquid cooling technology and edge computing architectures, significantly enhancing server cooling efficiency. The adoption of these green computing technologies effectively reduced energy consumption and carbon emissions from centralized computing. This enabled Chinese tech corporations to pursue high computing power while achieving sustainable development, ultimately enhancing overall ESG performance.

Figure 2. Examining the null hypothesis that AICP is not a Granger cause of ESG



Source: own graph in EViews 12; Notes: The research counts p-values by using 1000 bootstrap repetitions. The solid line means the bootstrap p-values, and the dashed line means p-value=0.1.

Figure 3. The coefficients of the influence from AICP to ESG

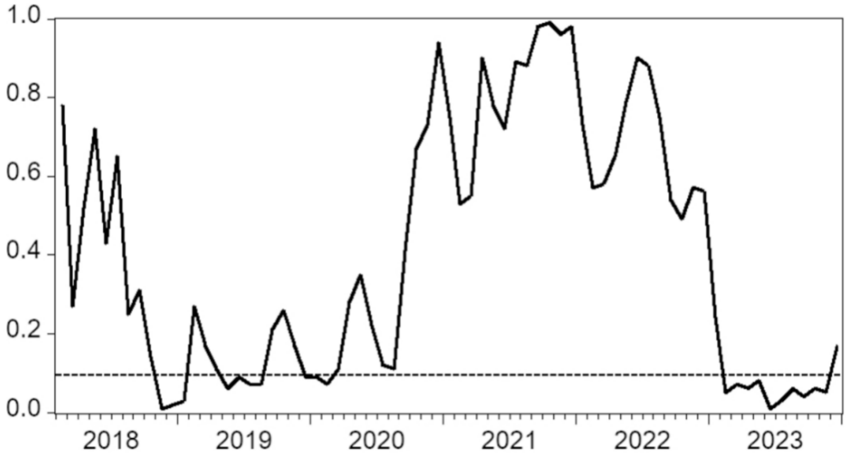


Source: own graph in EViews 12; Notes: The shadow represents the interval where AICP has significant Granger causality to ESG.

In contrast to the previous period, from May to November 2023, both AICP and ESG exhibited a significant downward trend, highlighting how a decline in AICP may limit the effectiveness of ESG strategies in key areas. According to a report by “China Energy Network” in July 2023, progress in the construction of some green intelligent data centers fell behind schedule, and the anticipated improvements in energy efficiency following retrofitting were not fully achieved (Yin et al., 2023). Consequently, the reduced availability of AICP hindered carbon emissions monitoring by lowering the efficiency of AI-driven environmental data analytics, impairing companies' ability to track and mitigate emissions in real-time. Additionally, the "China Computing Power Development Index White Paper (2023)"noted that the market for general-purpose servers and CPUs supporting AI technology contracted in 2023. This decline in AICP also affected supply chain optimization, as AI-driven logistics and resource allocation require substantial computing power to enhance sustainability performance. Furthermore, the slowdown in AI investment disrupted corporate sustainable practices, particularly AI-powered automation and intelligent decision-making, which contribute to ESG goal-setting, compliance tracking, and energy efficiency improvements (Yin et al., 2024). In summary, AI technology plays a crucial role in enhancing supply chain management and reducing environmental impacts, and thus, a decline in AICP investment disrupts ESG outcomes across multiple dimensions.

Figure 4 and 5 present the P-values and the direction of ESG's impact on AICP. From October 2018 to January 2019, from April to August 2019, and from February to November 2023, at a 10% significance level, the hypothesis that ESG does not Granger cause AICP is rejected. During the periods from October 2018 to January 2019 and from April to August 2019, ESG's impact on AICP was positive. However, from February to November 2023, ESG exhibited a declining trend, whereas AICP first increased and then declined.

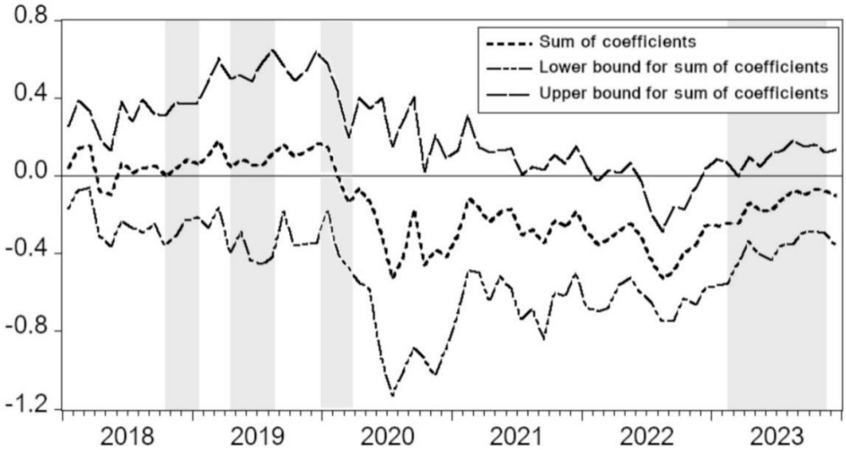
Figure 4. Examining the null hypothesis that ESG is not a Granger cause of AICP



Source: own graph in EViews 12; Notes: The research counts p-values by using 1000 bootstrap repetitions. The solid line means the bootstrap p-values, and the dashed line means p-value=0.1.

From October 2018 to January 2019, both ESG and AICP exhibited an upward trend, with ESG having a significant positive impact on AICP. During this period, the China Securities Regulatory Commission mandated enhanced ESG disclosure for listed companies and introduced the CSI 180 ESG index as the first ESG development index, highlighting ESG's growing importance in China's capital markets (Wang & Li, 2023). To meet ESG standards and pursue high ESG ratings, companies became more inclined to utilize AICP to optimize resource allocation (Zhou & Liu, 2023). Consequently, the improvement in ESG spurred companies to accelerate the development and application of AICP, aligning with their sustainability objectives (Annesi et al., 2024). Additionally, in 2018, the Chinese government issued the "Guiding Opinions on Promoting Green and Intelligent Technology Innovation"(Guo et al., 2020). Under this policy, several companies adopted AI and big data for energy management and built green computing centers, enhancing public perception of the green economy's role in AICP development. These actions enhanced the influence of the green economy and ESG in AICP growth, leading to a positive impact of ESG on AICP.

Figure 5. The coefficients of the influence from ESG to AICP



Source: own graph in EViews 12; Notes: The shadow represents the interval where ESG has significant Granger causality to AICP

From April to August 2019, both ESG and AICP demonstrated the same upward trend, which can be attributed to policy support and synergetic development within the AICP sector. Firstly, the development of green finance significantly supported AICP growth. For instance, the "China ESG Development White Paper" revealed that by 2019, 12% of public funds in China had established their own ESG evaluation systems, and 40% of surveyed institutions showed significant interest in ESG investments (Zhu, 2023). The heightened emphasis on ESG reduced the financing costs for green projects, thereby encouraging firms to increase investment in low-energy, high-computing power equipment to meet ESG requirements. Moreover, rising ESG demand directly facilitated the application and advancement of AICP (Rane et al., 2024). In July 2019, Alibaba's cloud division collaborated with environmental initiatives, using AI to optimize energy management and scheduling, which improved data center energy efficiency (Yun et al., 2020). This not only aligned with ESG objectives but also propelled the advancement of AICP, laying the foundation for technological optimization and cost reduction. These actions and examples illustrate the positive synergy between ESG and AICP, leading to a concurrent rise in both during this period. Moreover, Between January and March 2020, the COVID-19 pandemic erupted globally, prompting Chinese companies to accelerate their digital transformation in response to economic downturn pressures (Abdusattorov, 2022). During this period, AI technology became a critical tool for businesses to tackle challenges, optimize operations, and mitigate risks (Agarwal et al., 2024). Many companies began leveraging AI to enhance production efficiency, implement targeted marketing, and improve supply chain management, directly driving the demand for AI computing power. Furthermore, during the pandemic, there was an increased demand from the government for health, safety, and environmental monitoring. The application of AI and big data in epidemic monitoring, prediction, and control rapidly expanded, further boosting the demand for computational power and fostering the development of AI technologies.

From February to November 2023, ESG exhibited an upward trend, while AICP initially increased and then declined, highlighting the dynamic relationship between corporate sustainability efforts and AI computing power investment. At the start of this period, the pursuit of ESG goals encouraged firms to increase investment in AI-driven solutions, such as carbon footprint tracking, energy efficiency optimization, and compliance monitoring, contributing to the initial rise in AICP. However, as these AI systems became integrated and operational, companies faced diminishing returns on additional AI investments, leading to a slowdown in AICP growth. Several economic and policy factors further contributed to this trend. First, the emergence of green credit risks created financial uncertainty, prompting companies to re-evaluate their ESG investment strategies. "Progress and Risk Prevention of Green Financing in China" indicated that concerns over green credit risk led banks to tighten funding support for ESG projects, impacting corporate ESG investment decisions (Zhang et al., 2024). Second, while major Chinese asset management firms initially increased funding for sustainable projects, they later diverted capital back to traditional fossil fuel sectors, reducing momentum in ESG-related financial flows (Meng et al., 2023). At the same time, the surge in AICP during the first half of 2023 was driven by government-backed initiatives, such as the "Overall Layout Plan for Digital China," which promoted digital transformation and intelligent infrastructure development (Guo & Zhang, 2024). However, in the second half of 2023, as firms reached a saturation point in AI-related ESG investments and operating costs remained high, AICP growth slowed. Additionally, global fintech risks prompted Chinese regulatory authorities to tighten IPO activities, which restricted tech sector financing and further reduced AICP expansion.

6. Conclusions and Policy Recommendations

This study investigated the complex relationship between China's AICP and corporate ESG performance. Initially, we conducted a full-sample Granger causality test to observe the relationship between the two. Then we used a parameter stability test and found that the relationship between AICP and ESG is unstable. To ensure the precision of our results, we applied a rolling-window subsample estimation for causality, which confirmed the existence of bidirectional causality. AICP has both positive and negative effects on ESG. Proponents argue that AICP can promote ESG development, while critics counter that intelligent computing centers are energy-intensive, which diminishes ESG's environmental benefits. Conversely, ESG also has both positive and negative effects on AICP.

Based on the ripple effects observed in the influence of AICP on corporate ESG, this study proposes meaningful policy recommendations. First, the government should provide targeted subsidies and tax incentives to encourage companies to establish AICP for optimizing ESG performance, especially with policy support for carbon emission monitoring and energy optimization. These policies should also focus on sector-specific strategies, such as incentivizing AI-driven ESG applications in renewable energy for monitoring grid efficiency, in financial services for sustainable investment analysis, and in manufacturing for optimizing resource utilization and waste reduction. Second, functional departments should develop energy efficiency standards for green data centers and standards for AI applications in ESG to ensure the sustainability of AICP and minimize AI computing's environmental impact. Furthermore, the government should promote inter-company collaboration by encouraging the shared use of AICP centers and establishing open data-sharing mechanisms. This could support broader social governance goals by fostering transparency and enabling smaller firms to access advanced AI-driven ESG tools, thus leveling the playing field across industries.Finally, integrating green finance incentives with AICP innovation is critical for driving corporate transformation. Financial institutions should be encouraged to issue green bonds and provide financing options tailored to AICP projects, such as those focused on energy management, pollution monitoring, or sustainable supply chain optimization. By aligning financial innovation with AI-enabled ESG practices, businesses can not only enhance their environmental performance but also build competitive advantages, such as improved sustainability reporting, streamlined decision-making processes, and greater appeal to environmentally conscious investors. These measures can significantly enhance the widespread adoption of AI computing capabilities in corporate ESG management, amplifying its positive "ripple effects" across industries while creating value for global managers and stakeholders.

7. Limitations and Further Research

While this study provides valuable insights into the relationship between AI computing power and corporate ESG performance, there are several limitations that should be addressed in future research. First, the analysis is primarily based on case data from China, which may limit the generalizability of the findings to other countries with different AI ecosystems and ESG regulatory environments. Future studies could benefit from incorporating cross-country comparative analysis to determine whether the observed trends are consistent across different regions. Second, the study does not account for potential mediating variables or external factors that may influence the relationship between AICP and ESG performance. For example, market conditions, technological developments, or the influence of corporate culture may play a role in shaping this interaction. Future research could expand the framework by including these factors to better understand the underlying mechanisms. Third, this study focused on the interaction between AICP and ESG performance in the context of large, publicly listed companies. It would be interesting to explore how smaller companies or different industry sectors engage with AI and ESG, as they may face distinct challenges and opportunities. Finally, although this study has contributed to the literature on AI and ESG, more research is needed to explore the long-term impacts of AI adoption on sustainability goals. This includes examining how AI can further optimize resource allocation, improve environmental governance, and enhance corporate social responsibility practices over extended periods. Future research could explore these themes through longitudinal studies and the integration of real-time data analytics

References

Abdusattorov, M., 2022. The impact of COVID-19 on the global economy and businesses. Innovative ways to organize a comprehensive response to crisis (Doctoral dissertation, Politecnico di Torino).

Agarwal, P., Swami, S. and Malhotra, S. K., 2024. Artificial intelligence adoption in the post COVID-19 new-normal and role of smart technologies in transforming business: a review. *Journal of Science and Technology Policy Management*, 15(3), pp.506-529. https://doi.org/10.1108/JSTPM-08-2021-0122.

Alfalih, A.A., 2023. ESG disclosure practices and financial performance: A general and sector analysis of SP-500 non-financial companies and the moderating effect of economic conditions. *Journal of Sustainable Finance & Investment*, 13(4), pp.1506–1533. https://doi.org/10.1080/20430795.2022.2150511.

Andrews, D.W., 1993. Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, pp.821-856. https://doi.org/10.2307/2951764.

Annesi, N., Battaglia, M., Ceglia, I. and Mercuri, F., 2024. Navigating paradoxes: building a sustainable strategy for an integrated ESG corporate governance. *Management Decision*. https://doi.org/10.1108/MD-10-2023-2006.

Avramov, D., Cheng, S., Lioui, A. and Tarelli, A., 2022. Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, 145(2), pp.642–664. https://doi.org/10.1016/j.jfineco.2021.09.009.

Balcilar, M., Ozdemir, Z.A. and Arslanturk, Y., 2010. Economic growth and energy consumption causal nexus viewed through a bootstrap rolling window. *Energy Economics*, 32(6), pp.1398–1410. https://doi.org/10.1016/j.eneco.2010.05.015.

Berg, F., Koelbel, J.F. and Rigobon, R., 2022. Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6), pp.1315–1344. https://doi.org/10.1093/rof/rfac033.

Burnaev, E., Mironov, E., Shpilman, A., Mironenko, M. and Katalevsky, D., 2023. Practical AI Cases for Solving ESG Challenges. *Sustainability*, 15(17), 12731. https://doi.org/10.3390/su151712731.

Cao, F., Su, C.W., Qin, M. and Moldovan, N.C., 2024. The investment of renewable energy: Is green bond a safe-haven to hedge U.S. monetary policy uncertainty?, *Energy*, 307, p. 132651. https://doi.org/10.1016/j.energy.2024.132651.

Clément, A., Robinot, É. and Trespeuch, L., 2022. Improving ESG scores with sustainability concepts. *Sustainability*, 14(20), 13154. https://doi.org/10.3390/su142013154.

Dadao, L., 2019. Preliminary study on development of some fields in fourteenth five year plan. *Bulletin of Chinese Academy of Sciences (Chinese Version)*, 34(10), pp.1143–1146.

Dayarathna, M., Wen, Y. and Fan, R., 2015. Data center energy consumption modeling: A survey. *IEEE Communications Surveys & Tutorials*, 18(1), pp.732–794. https://doi.org/10.1109/COMST.2015.2481183.

De Stefano, V., 2019. "Negotiating the Algorithm": Automation, artificial intelligence, and labor protection. Comp. Lab. L. & Pol'y J., 41, p.15. https://doi.org/10.2139/ssrn.3178233.

Escrig-Olmedo, E., Fernández-Izquierdo, M.Á., Ferrero-Ferrero, I., Rivera-Lirio, J.M. and Muñoz-Torres, M.J., 2019. Rating the raters: Evaluating how ESG rating agencies integrate sustainability principles. *Sustainability*, 11(3), Article 3. https://doi.org/10.3390/su11030915.

Guo, R., Lv, S., Liao, T., Xi, F., Zhang, J., Zuo, X., ... and Zhang, Y., 2020. Classifying green technologies for sustainable innovation and investment. *Resources, Conservation and Recycling*, 153, 104580. https://doi.org/10.1016/j.resconrec.2019.104580.

Guo, Y. and Zhang, T., 2024. The Present of Digital Government: Insights From Chinese Practices. *In Emerging Developments and Technologies in Digital Government* (pp.23-43). IGI Global. https://doi.org/10.4018/979-8-3693-2363-2.ch002.

Hilb, M., 2020. Toward artificial governance? The role of artificial intelligence in shaping the future of corporate governance. *Journal of Management and Governance*, 24(4), pp.851–870. https://doi.org/10.1007/s10997-020-09519-9.

Khoruzhy, L.I., Semenov, A.V., Averin, A.V. and Mustafin, T.A., 2022. ESG investing in the AI era: Features of developed and developing countries. *Frontiers in Environmental Science*, 10, 951646. https://doi.org/10.3389/fenvs.2022.951646.

Lee, S.U., Perera, H., Liu, Y., Xia, B., Lu, Q., Zhu, L., Cairns, J. and Nottage, M., 2024. Integrating ESG and AI: A comprehensive responsible AI assessment framework (arXiv:2408.00965). *arXiv.* https://doi.org/10.1007/s43681-025-00741-5.

Li, G., Sun, Z., Wang, Q., Wang, S., Huang, K., Zhao, N., Di, Y., Zhao, X. and Zhu, Z., 2023. China's green data center development: Policies and carbon reduction technology path. *Environmental Research*, 231, 116248. https://doi.org/10.1016/j.envres.2023.116248.

Li, X. and Su, C.W., 2024. Evaluating the impact of multiple uncertainty shocks on China's airline stocks volatility: A novel joint quantile perspective, *Journal of Air Transport Management*, 121, p. 102688. https://doi.org/10.1016/j.jairtraman.2024.102688.

Liu, F., Su, C.W., Qin, M. and Umar, M., 2024. Bitcoin: a Ponzi scheme or an emerging inflation-fighting asset?, *Technological and Economic Development of Economy*, pp.1-21. https://doi.org/10.3846/tede.2024.19300.

Meng, T., Yahya, M.H.D.H., Ashhari, Z.M. and Yu, D., 2023. ESG performance, investor attention, and company reputation: Threshold model analysis based on panel data from listed companies in China. *Heliyon. https://doi.org/10.1016/j.heliyon.2023.e20974.*

Nyblom, J., 1989. Testing for the constancy of parameters over time. *Journal of the American Statistical Association*, 84(405), pp.223–230. https://doi.org/10.1080/01621459.1989.10478759.

Pappaterra, M. J., 2022. A Review of Literature and Public Datasets for the Application of Artificial Intelligence in the Railway Industry.

Qin, M., Chang, H.L., Su, C.W., Racataian, R.I. and Craciun, A.F., 2024a. Substitution or Creation? Identifying the Role of Artificial Intelligence in Employment, *Technological and Economic Development of Economy*, pp.1-22. https://doi.org/10.3846/tede.2024.21929.

Qin, M., Wan, Y., Dou, J. and Su, C.W., 2024. Artificial Intelligence: Intensifying or mitigating unemployment?, *Technology in Society*, 79, p. 102755. https://doi.org/10.1016/j.techsoc.2024.102755.

Qin, M., Su, A.H., Li, R. and Su, C.W., 2024. Speculation, climate or pandemic: Who drives the Chinese herbal medicine bubbles?, *China Economic Review*. https://doi.org/10.1016/j.chieco.2024.102213.

Rai, D.H., 2024. Artificial Intelligence Through Time: A Comprehensive Historical Review.

Rane, N., Choudhary, S. and Rane, J., 2024. Artificial intelligence driven approaches to strengthening Environmental, Social, and Governance (ESG) criteria in sustainable business practices: a review. *Social, and Governance (ESG) criteria in sustainable business practices: a review* (May 27, 2024). https://doi.org/10.2139/ssrn.4843215.

Pesaran, M.H. and Timmermann, A., 2005. Small sample properties of forecasts from autoregressive models under structural breaks. *Journal of Econometrics*, 129(1-2), pp.183-217. https://doi.org/10.1016/j.jeconom.2004.09.007.

Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V. and Floridi, L., 2021. The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *In Springer International Publishing*, pp.47-79. https://doi.org/10.1007/978-3-030-81907-1_5.

Shukur, G. and Mantalos, P., 2004. Size and power of the RESET test as applied to systems of equations: A bootstrap approach. *Journal of Modern Applied Statistical Methods*, 3, pp.370-385. https://doi.org/10.22237/jmasm/1099267800.

Su, C.W., Liu, X., Vătavu, S. and Dumitrescu Peculea, A., 2024. Will peer-to-peer online lending affect the effectiveness of monetary policy?, *Technological and Economic Development of Economy*, pp.1-22. https://doi.org/10.3846/tede.2024.19334.

Su, C.W., Liu, X., Qin, M. and Umar, M., 2024. Is the Uncertainty Economic Policy an Impediment or an Impetus to Technological Innovation? *Emerging Markets Finance and Trade*. Published Online. https://doi.org/10.1080/1540496X.2024.2324201.

Su, C.W., Lv, S., Qin, M. and Norena-Chavez, D., 2024. Uncertainty and Credit: The Chicken or the Egg Causality Dilemma. *Emerging Markets Finance and Trade*. Published Online. https://doi.org/10.1080/1540496X.2024.2318299.

Su, C.W., Yang, S., Dumitrescu Peculea, A., Biţoiu, T.I. and Qin, M., 2024. Energy imports in turbulent eras: Evidence from China, *Energy*, 306(15), p. 132586. https://doi.org/10.1016/j.energy.2024.132586.

Su, C.W., Song, X.Y., Qin, M., Lobonţ, O.R. and Umar, M., 2024. Optimistic or pessimistic: How do investors impact the green bond market? *The North American Journal of Economics and Finance*, 102248. https://doi.org/10.1016/j.najef.2024.102248.

Su, C.W., Song, X.Y., Qin, M. and Lobonţ, O.R., 2024. Green intent or black smoke: Exploring investor sentiment on sustainable development. *International Journal of Finance & Economics*. Published Online. DOI: 10.1002/ijfe.2998. https://doi.org/10.1002/ijfe.2998.

Su, C.W., Qin, M., Tao, R., Shao, X.F., Albu, L.L. and Umar, M., 2020. Can bitcoin hedge the risks of geopolitical events?. *Technological Forecasting and Social Change*, 159, 120182. https://doi.org/10.1016/j.techfore.2020.120182.

Stahl, B.C. and Wright, D., 2018. Ethics and privacy in AI and big data: Implementing responsible research and innovation. *IEEE Security & Privacy*, 16(3), pp.26–33. https://doi.org/10.1109/MSP.2018.2701164.

Wang, J. and Li, L., 2023. Climate risk and Chinese stock volatility forecasting: Evidence from ESG index. *Finance Research Letters*, 55, 103898. https://doi.org/10.1016/j.frl.2023.103898.

Wu, F., Lu, C., Zhu, M., Chen, H., Zhu, J., Yu, K., Li, L., Li, M., Chen, Q. and Li, X., 2020. Towards a new generation of artificial intelligence in China. *Nature Machine Intelligence*, 2(6), pp.312–316. https://doi.org/10.1038/s42256-020-0183-4.

Yang, C. and Huang, C., 2022. Quantitative mapping of the evolution of AI policy distribution, targets and focuses over three decades in China. *Technological Forecasting and Social Change*, 174, 121188. https://doi.org/10.1016/j.techfore.2021.121188.

Yin, F., Xiao, Y., Cao, R. and Zhang, J., 2023. Impacts of ESG disclosure on corporate carbon performance: Empirical evidence from listed companies in heavy pollution industries. *Sustainability*, 15(21), 15296. https://doi.org/10.3390/su152115296.

Yin, T., Zhang, Z. and Zhang, T., 2024. RISC-V leads the future: Evolution and outlook of CPU architecture. Science and Technology of Engineering, *Chemistry and Environmental Protection*, 1(9), Article 9. https://doi.org/10.61173/sfv24n83.

Yun, J. J., Zhao, X., Park, K. and Shi, L., 2020. Sustainability condition of open innovation: Dynamic growth of alibaba from SME to large enterprise. *Sustainability*, 12(11), 4379. https://doi.org/10.3390/su12114379.

Zhang, A.Y. and Zhang, J.H., 2024. Renovation in environmental, social and governance (ESG) research: The application of machine learning. *Asian Review of Accounting*, 32(4), pp.554-572. https://doi.org/10.1108/ARA-07-2023-0201.

Zhang, G. and Ravishankar, M.N., 2019. Exploring vendor capabilities in the cloud environment: A case study of Alibaba Cloud Computing. Information & Management, 56(3), pp.343–355. https://doi.org/10.1016/j.im.2018.07.008.

Zhang, J., Song, Z. and Nedopil, C., 2024. China green finance status and trends 2023-2024. Griffith Asia Institute, Griffith University (Brisbane) and Green Finance & Development Center, FISF Fudan University (Shanghai).https://doi.org/10.25904/1912/5205.

Zhang, N., Duan, H., Guan, Y., Mao, R., Song, G., Yang, J. and Shan, Y., 2024. The “Eastern Data and Western Computing” initiative in China contributes to its net-zero target. *Engineering*. https://doi.org/10.1016/j.eng.2024.08.010.

Zhou, H. and Liu, J., 2023. Digitalization of the economy and resource efficiency for meeting the ESG goals. *Resources Policy*, 86, 104199. https://doi.org/10.1016/j.resourpol.2023.104199.

Zhu, L., 2023. How does the digital economy empower corporate ESG? Evidence from China. *Advances in Economic Development and Management Research*, 1(1), 45-61. https://doi.org/10.61935/aedmr.1.1.2023.P45.