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The Dual Role of Artificial Intelligence in Sustainability Governance: Time–Frequency Evidence from Climate Response and Infectious Disease Attention in China

Ruiqian Zhang [1], Jiayi Lyu [2,*], Yan Chen [2] and Zhengzheng Li [3]

1 School of Economics and Management, Shanghai Maritime University, Shanghai 200135, China
2 School of Economics and Management, Beijing University of Posts and Telecommunications, Beijing 100876, China
3 Faculty of Economics and Business Administration, West University of Timisoara, Timisoara 300223, Romania; 100876lizhengzheng@qdu.edu.cn
* Correspondence: ljy314865315@gmail.com

Abstract

Artificial intelligence (AI) is increasingly regarded as a key instrument for sustainability governance, but its role may differ across risk domains. Rather than functioning solely as an anticipatory tool, AI may also develop reactively in response to risk shocks. Using monthly Chinese data from January 2013 to December 2023, this study examines the dual role of AI in sustainability governance by analyzing its time–frequency relationships with climate-related government response and infectious disease-related market attention. The continuous wavelet transform and partial wavelet coherence are employed, with the World Uncertainty Index controlled. The results show that AI-sector development is positively associated with both risk-related signals, but the lead–lag patterns differ substantially. In the climate-response domain, the relationship shifts from risk-signal precedence in 2015–2016 to AI-sector precedence in short-term bands after 2020, suggesting that AI-related capacity may have become increasingly embedded in anticipatory climate governance. In contrast, infectious disease-related attention mainly precedes AI-sector movements, especially during 2017–2018 and the COVID-19 period, indicating a more reactive role of AI in public health risk contexts. These findings do not provide causal evidence that AI directly reduces physical climate risks or epidemiological burdens. Instead, they reveal the dual role of AI as both a response to sustainability-related risk shocks and a potential contributor to forward-looking governance capacity. This study contributes to AI and sustainability governance research by clarifying the conditions and boundaries under which AI shifts from reactive crisis response toward anticipatory risk preparedness.

Keywords: artificial intelligence; anticipatory governance; sustainability governance; climate response; infectious disease attention; wavelet analysis

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1. Introduction

Since the beginning of the 21st century, sustainability governance has faced increasingly complex and interconnected risks [1–3]. Climate-related disasters, public health emergencies, economic uncertainty, and technological disruption often interact across ecological, social, and economic systems [4–6]. These compound risks expose the limitations of conventional governance models that rely mainly on post-event response. A key challenge for sustainable development is therefore how governance systems can detect, interpret, and prepare for risks before they fully materialize [7,8].

Climate-related governance responses and infectious disease market attention represent two core sustainability-related risk signal domains where this governance challenge is prominent [9]. Climate-related events, such as extreme temperatures, floods, droughts, typhoons, and air pollution, place growing pressure on environmental management, urban resilience, and economic transformation [10]. Infectious disease outbreaks reveal the vulnerability of public health systems to uncertain, fast-moving, and cross-regional shocks. Although both domains are central to sustainability governance, they differ in risk mechanisms and governance requirements. Climate-related risks are often supported by continuous meteorological and environmental data, making them more suitable for prediction and early warning. Infectious disease risks, by contrast, involve pathogen evolution, population mobility, medical capacity, behavioral responses, and institutional coordination, which makes anticipatory governance more difficult [11,12].

Against this background, artificial intelligence (AI) has been widely viewed as a promising tool for sustainability governance [13,14]. By supporting real-time monitoring, pattern recognition, forecasting, early warning, and resource allocation [15], AI may improve the ability of governments and organizations to identify and manage emerging risks [16,17]. In climate governance, AI has been applied to extreme weather forecasting, air quality prediction, disaster warning, carbon monitoring, energy-system optimization [18], and early risk warning systems [19]. In public health governance, AI has been used for epidemic forecasting, diagnostic support, vaccine and drug development, and medical-resource allocation. These applications suggest that AI may contribute not only to emergency response, but also to the shift from reactive crisis management to anticipatory risk governance [20–22].

However, the relationship between AI and risk governance is not one-directional [23,24]. AI may support risk management, but risk shocks may also stimulate AI-related investment and technological development. During periods of heightened risk, governments may increase demand for intelligent monitoring and emergency-management tools, firms may accelerate AI innovation, and capital markets may revalue AI-related industries [16,25,26]. As AI-related capacity matures, it may also become embedded in risk detection, early warning, and policy response systems [27]. Therefore, the key issue is not simply whether AI reduces risks, but whether AI functions mainly as a reactive tool, an adaptive component, or an anticipatory governance capacity.

This distinction is important because AI-enabled risk governance remains difficult to measure. Continuous monthly data on the actual deployment of AI in specific governance systems are rarely available. Similarly, physical climate disaster severity, epidemiological burden, government response intensity, media attention, and market sensitivity represent different dimensions of risk. This study therefore does not claim to directly measure physical climate risk, actual infectious disease burden, or real AI deployment in governance systems. Instead, it focuses on observable sustainability-related risk signals and AI-sector development. Climate-related government response is treated as a signal of institutional attention and response intensity, while infectious disease-related market attention is treated as a signal of financial and media sensitivity to disease-related shocks.

Existing studies have contributed substantially to research on AI and risk management. Some studies examine AI applications in disaster forecasting, emergency logistics, environmental monitoring, and public health management. Others show how major risk events may stimulate technological innovation and digital transformation. However, three gaps remain. First, most studies focus on single risk domains and pay limited attention to the heterogeneous role of AI across sustainability-related risks. Second, AI is often evaluated from a static perspective, although risk governance varies across time scales. Third, existing research rarely distinguishes reactive AI deployment after risk shocks from anticipatory AI capacity before risks fully unfold.

This study addresses three research questions:

RQ1: Does AI-sector development act as a reactive, adaptive, or anticipatory force in relation to sustainability-related risk signals?

RQ2: Do climate-related government responses and infectious disease-related market attention show different time–frequency relationships with AI-sector development?

RQ3: What do these differences reveal about the conditions and boundaries under which AI may support anticipatory governance for sustainability?

To answer these questions, this study employs continuous wavelet transform and partial wavelet coherence analysis to examine the dynamic co-movement and phase-based lead–lag relationships between AI-sector development and two sustainability-related risk signals in China. Wavelet analysis is suitable because risk-related and market-related data are often noisy, non-stationary, and heterogeneous across time scales. It enables localized associations to be observed in both time and frequency domains. Importantly, this study interprets wavelet coherence and phase differences as evidence of time–frequency association and temporal precedence, rather than structural causality. Using monthly Chinese data from January 2013 to December 2023, the analysis focuses on the CSI Artificial Intelligence Index, a climate-related government response index, an infectious disease-related market attention index, and the World Uncertainty Index as a control variable.

This study contributes to the literature in three ways. First, it shifts the focus of AI and sustainability governance research from whether AI directly reduces risks to whether AI is associated with reactive, adaptive, or anticipatory governance patterns. This provides a more nuanced framework for understanding the role of AI in sustainability transitions.

Second, this study contributes to the measurement debate in AI-enabled risk governance. Instead of treating proxy variables as direct measures of physical disaster severity, epidemiological burden, or actual AI deployment, it explicitly defines them as observable signals of climate-related government response, infectious disease-related market attention, and AI-sector development. This clarification supports a more cautious and transparent interpretation of the empirical results.

Third, this study provides time–frequency evidence on the heterogeneous relationship between AI and two sustainability-related domains. By comparing climate response and infectious disease attention, it shows that AI may be more readily embedded in anticipatory governance when risks are data-intensive, continuously monitored, and compatible with prediction and early warning. In public health contexts, where uncertainty, institutional coordination, and social behavior play larger roles, AI may remain more reactive.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the methodology. Section 4 describes the data and measurement boundaries. Section 5 presents the empirical findings. Section 6 discusses mechanisms and policy implications, then concludes the paper.

2. Literature Review

2.1. Sustainability-Related Governance Challenges

The intensification of climate change and the increasing frequency of infectious disease outbreaks, as representative sustainability-related governance challenges, are severely eroding the foundations of natural capital. Climate change not only causes substantial economic losses directly through extreme weather disasters, including floods, droughts, and heatwaves [9], but also indirectly amplifies infectious disease risks by altering ecosystem structures and functions [12]. For example, biodiversity loss has fragmented wildlife habitats, increasing the frequency of contact between humans and pathogen hosts and thereby elevating the likelihood of outbreaks of infectious diseases such as COVID-19, SARS, and Ebola [28,29]. These interconnected risks collectively challenge traditional environmental governance models that are primarily oriented toward single-risk management approaches [30,31]. Consequently, identifying effective governance tools capable of simultaneously addressing complex environmental risks, including climate change and infectious disease outbreaks, has become essential for ensuring the successful transition toward an environmentally sustainable economy.

2.2. Artificial Intelligence and Sustainable Governance

With the rapid advancement of AI technologies, their role in addressing environmental risks has become increasingly prominent. Vasiliev et al. [27] argued that AI, through its superior capabilities in data processing and analysis, can accurately predict the timing, location, and impacts of disasters, thereby improving the efficiency and precision of emergency responses. Gevaert et al. [32] demonstrated that machine learning algorithms can forecast seismic activity by analyzing historical and real-time sensor data, facilitating timely warning systems. Similarly, Rolnick et al. [33] highlighted the capacity of predictive modeling to improve climate change forecasting and hurricane path prediction, thereby strengthening early warning systems and supporting effective resource allocation and post-disaster recovery. Bukhari et al. [34] further pointed out that reinforcement learning algorithms optimize real-time decision-making in emergency situations by improving the allocation of personnel and critical supplies in high-risk areas. In the field of infectious diseases, Shamman [35] and Balasubramanian et al. [36] emphasized that during the COVID-19 pandemic, AI enhanced global public health responses by predicting disease transmission patterns, accelerating vaccine development, and advancing intelligent diagnostic tools.

At the same time, extreme risk scenarios have also created unique conditions for the evolution of AI technologies. The increasing complexity of systemic risks has accelerated the advancement of intelligent systems. A growing body of research suggests that sudden or exceptionally severe risks often function as catalysts for technological innovation. For instance, Yao et al. [37] and Jin et al. [38] observed that the COVID-19 pandemic stimulated the widespread adoption of machine learning algorithms across applications ranging from epidemic containment and pathogen analysis to epidemic trajectory forecasting. Chen et al. [39] and McDonald et al. [40] further highlighted that the continuously evolving and increasingly complex epidemiological data accelerated the advancement of AI algorithms, with dynamic algorithm-driven models emerging as powerful tools for responding to rapidly changing epidemic conditions. Within the context of climate change, Yao et al. [41] noted that the increasing frequency of extreme weather events has driven deep learning models to assimilate multisource meteorological data more effectively. Bukhari et al. [34] reported that, under continued global warming, the integration of increasingly frequent flood-related data enabled Google's global flood forecasting system to generate highly accurate simulations up to 72 h in advance, thereby providing critical early warning capabilities for vulnerable regions.

More importantly, these two strands of research suggest that the relationship between AI and risk governance should be understood as interactive rather than one-directional. On the one hand, AI can support risk governance by improving monitoring, prediction, early warning, and resource allocation. On the other hand, risk shocks can reshape technological demand, policy priorities, market expectations, and innovation trajectories in the AI sector. Existing studies have increasingly recognized this reciprocal relationship, but important debates remain. Some scholars emphasize the proactive role of AI in strengthening anticipatory governance capacity [33], especially in data-intensive domains such as climate monitoring and disaster forecasting. Others caution that AI is often mobilized only after major crises occur, meaning that its development may reflect reactive adaptation to risk shocks rather than genuine ex ante governance capacity [42,43]. This debate is particularly relevant for sustainability governance, because different risks vary in their observability, predictability, institutional complexity, and dependence on social behavior. Therefore, whether AI functions as an anticipatory governance tool or as a reactive response mechanism may differ significantly across risk domains.

2.3. Brief Review

Although previous studies have examined AI applications in risk management and the risk-induced evolution of AI technologies, the existing literature still leaves several important gaps. First, most studies focus on single risk domains and pay insufficient attention to whether the role of AI differs across sustainability-related risks. In particular, limited research has compared climate-related governance contexts with infectious disease-related public health contexts, even though these domains differ substantially in data availability, predictability, institutional coordination, and governance requirements. Second, existing studies often discuss AI as either a governance tool or an innovation outcome, but rarely examine the dynamic interaction between these two roles. As a result, the co-evolutionary relationship between AI development and risk-related governance signals remains underexplored. Third, most research evaluates AI from a relatively static perspective, while risk governance itself evolves across different time scales. Whether AI behaves as a reactive response after risk shocks, an adaptive component that co-moves with risk signals, or an anticipatory capacity embedded in forward-looking governance systems remains insufficiently examined.

To address these gaps, this study develops a dual-role perspective on AI in sustainability governance. Rather than assuming that AI directly reduces environmental or public health risks, this study investigates how AI-sector development interacts with observable risk-related governance signals over time and across frequencies. Specifically, it compares climate-related government response and infectious disease-related market attention in China from January 2013 to December 2023. By employing continuous wavelet transform and partial wavelet coherence analysis, this study identifies time–frequency co-movement and phase-based lead–lag patterns between AI-sector development and the two risk-related signals. This approach allows us to distinguish whether AI appears mainly as a reactive response to risk shocks or as a potential contributor to anticipatory governance capacity. In doing so, the study clarifies the conditions and boundaries under which AI may shift from crisis-driven technological response toward forward-looking sustainability governance.

3. Wavelet Analysis

3.1. Methodological Rationale and Settings

Wavelet analysis provides a useful framework for examining the dynamic relationship between AI-sector development and sustainability-related risk signals in both the time and frequency domains. Compared with Fourier analysis, which decomposes a series only in the frequency domain and is more suitable for stationary processes, wavelet analysis can capture localized variations in non-stationary time series [44–46]. This feature is particularly relevant for risk-related and market-related variables, which often display abrupt changes, volatility clustering, and heterogeneous cycles.

This study uses the continuous wavelet transform (CWT) rather than the discrete wavelet transform (DWT), because CWT is better suited for identifying localized co-movement and phase-based lead–lag patterns in noisy time series [47,48]. The complex Morlet wavelet is selected as the mother wavelet because it provides a good balance between time and frequency localization and allows the interpretation of phase differences. Statistical significance is assessed at the 5% level using 500 Monte Carlo simulations. Given the monthly frequency of the data, this study classifies the frequency bands into short-term cycles of 1–2 years, medium-term cycles of 2–4 years, and long-term cycles of 4–8 years.

The cone of influence (COI) is used to indicate regions where edge effects may distort the wavelet estimates. Therefore, the interpretation focuses mainly on statistically significant regions outside, or clearly away from, the COI. Since the sample contains 132 monthly observations, results in the 4–8 year frequency band are treated as exploratory and interpreted with caution. Importantly, wavelet coherence and phase differences are used to identify time–frequency associations and temporal precedence, rather than structural causality.

3.2. The Continuous Wavelet Transform (CWT)

For a time series $x(t) \in L^2(R)$, the continuous wavelet transform is defined as:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\psi^*_{\tau,s}(t)dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \quad (1)$$

where $\psi(t)$ denotes the mother wavelet, $\psi_{\tau,s}(t)$ is the wavelet basis function, $*$ indicates complex conjugation, τ is the translation parameter, and $s > 0$ is the scale parameter. The scale parameter is inversely related to frequency and can be converted into a corresponding time period.

The original series can be reconstructed from its wavelet coefficients when the admissibility condition is satisfied:

$$0 < C_\psi = \int_0^{+\infty} \frac{|\hat{\psi}(f)|^2}{f} df < +\infty \quad (2)$$

where $\hat{\psi}(f)$ is the Fourier transform of $\psi(t)$. Under this condition, the wavelet transform preserves the energy of the original series:

$$||x||^2 = \frac{1}{C_\psi}\int_0^{+\infty}\int_{-\infty}^{+\infty} |W_x(\tau, s)|^2 \, d\tau \frac{ds}{s^2} \quad (3)$$

This property makes CWT suitable for identifying localized variations in AI-sector development and sustainability-related risk signals across different time scales.

3.3. Wavelet Coherence and Partial Wavelet Coherence

Let AI denote AI-sector development and let Y denote a sustainability-related risk signal. In this study, Y refers either to climate-related government response or to infectious disease-related market attention. The cross-wavelet transform between AI and Y is defined as:

$$W_{AI,Y}(\tau, s) = W_{AI}(\tau, s)W^*_Y(\tau, s) \quad (4)$$

where $W_{AI}(\tau, s)$ and $W_Y(\tau, s)$ are the continuous wavelet transforms of AI and Y, respectively, and $*$ indicates complex conjugation.

The cross-wavelet power is given by:

$$|W_{AI,Y}(\tau, s)| = |W_{AI}(\tau, s)||W^*_Y(\tau, s)| \quad (5)$$

Cross-wavelet power identifies regions where the two variables share high common power in the time–frequency domain. However, high common power does not necessarily imply a stable co-movement relationship. Therefore, squared wavelet coherence is used to measure the localized correlation between the two series. Following Torrence and Webster [49], squared wavelet coherence is defined as:

$$R^2_{AI,Y}(\tau,s) = \frac{\mid S\left(s^{-1}W_{AI,Y}(\tau,s)\right)\mid^2}{S\left(s^{-1}\mid W_{AI}(\tau,s)\mid^2\right)S\left(s^{-1}\mid W_Y(\tau,s)\mid^2\right)} \tag{6}$$

where S denotes the smoothing operator. The value of $R^2_{AI,Y}(\tau, s)$ ranges from 0 to 1. A value closer to 1 indicates stronger localized co-movement between AI and Y.

To reduce the influence of common global uncertainty shocks, this study introduces the World Uncertainty Index (WUI) as a control variable and employs partial wavelet coherence. Following Aguiar-Conraria and Soares [50], squared partial wavelet coherence is expressed as:

$$R^2_{AI,Y|\mathrm{WUI}}(\tau,s) = \frac{\mid \mathrm{R_{AI,Y}}(\tau,s) - \mathrm{R_{AI,WUI}}(\tau,s)\mathrm{R^*_{Y,WUI}}(\tau,s)\mid^2}{\left(1-\mid \mathrm{R_{AI,WUI}}(\tau,s)\mid^2\right)\left(1-\mid \mathrm{R_{Y,WUI}}(\tau,s)\mid^2\right)} \tag{7}$$

where $R_{AI,Y}(\tau, s)$, $R_{AI,WUI}(\tau, s)$, and $R_{Y,WUI}(\tau, s)$ denote the complex wavelet coherencies between the corresponding variables. Controlling for WUI helps reduce the influence of common global uncertainty shocks, although it cannot eliminate all potential sources of omitted-variable bias. Therefore, the partial wavelet coherence results are interpreted as conditional time–frequency associations rather than causal estimates.

3.4. Partial Wavelet Coherence Phase Difference

Wavelet coherence measures the strength of localized co-movement, but it does not indicate which variable leads or lags. To examine the temporal ordering between AI-sector development and sustainability-related risk signals, this study uses the phase difference derived from complex partial wavelet coherency. The phase difference is defined as:

$$\phi_{\mathrm{AI,Risk|WUI}}(\tau,s) = \mathrm{atan}\,2\left(\Im\left[\rho_{AI,Y|WUI}(\tau,s)\right],\Re\left[\rho_{AI,Y|WUI}(\tau,s)\right]\right) \tag{8}$$

where $\rho_{AI,Y|WUI}(\tau, s)$ denotes the complex partial wavelet coherency between AI and Y conditional on WUI. $\Re(\cdot)$ and $\Im(\cdot)$ denote the real and imaginary parts, respectively. The phase difference $\phi_{AI,Y|WUI}(\tau, s)$ lies within the interval $[-\pi, \pi]$.

The phase difference is interpreted as follows:

$$\phi_{\mathrm{AI,Y|WUI}}(\tau,s) \approx 0$$

indicates that AI and Y move in the same direction.

$$\phi_{\mathrm{AI,Y|WUI}}(\tau,s) \approx \pi \mathrm{or} \phi_{\mathrm{AI,Y|WUI}}(\tau,s) \approx -\pi$$

indicates that AI and Y move in opposite directions.

Under the variable ordering used in this study:

$$0 \le \phi_{\mathrm{AI,Y|WUI}}(\tau,s) \le \frac{\pi}{2} \tag{9}$$

indicates that AI positively precedes the risk-related signal Y.

$$-\frac{\pi}{2} \le \phi_{\mathrm{AI,Y|WUI}}(\tau,s) \le 0 \tag{10}$$

indicates that the risk-related signal Y positively precedes AI.

Phase differences in the following intervals indicate lead–lag relationships under an anti-phase pattern:

$$\frac{\pi}{2} \leq \phi_{AI,Y|WUI}(\tau, s) \leq \pi \tag{11}$$

and

$$-\pi \leq \phi_{AI,Y|WUI}(\tau, s) \leq -\frac{\pi}{2} \tag{12}$$

That is, the two variables move in opposite directions, while one variable still precedes the other in time.

These phase-based interpretations are used to distinguish whether AI-sector development appears mainly as a reactive response to risk-related signals or as a potential contributor to anticipatory governance capacity. They should be understood as temporal precedence patterns, not as evidence that AI causally reduces physical climate risks or epidemiological burdens. For a more detailed explanation of the wavelet method, please refer to the Appendix A at the end of the paper.

4. Data

4.1. Research Context

This study selects China as the empirical context for examining the dual role of artificial intelligence (AI) in sustainability governance. China is a suitable case for two main reasons. First, China faces multiple sustainability-related challenges, including climate-related disasters, public health emergencies, economic volatility, and external uncertainty. These challenges create a context in which risk-related governance signals may interact with technological development. Second, China has actively promoted AI innovation and digital governance in recent years, creating conditions for AI-sector development to become increasingly connected with monitoring, early warning, emergency response, and policy coordination. Therefore, China provides a valuable setting for analyzing whether AI appears mainly as a reactive response to risk shocks or as a potential contributor to anticipatory governance capacity.

4.2. Variable Definition and Measurement Boundaries

This study uses monthly Chinese data from January 2013 to December 2023 to investigate the time–frequency co-movement and phase-based lead–lag relationships among AI-sector development, climate-related government response, infectious disease-related market attention, and global uncertainty. All variables are seasonally adjusted where necessary and standardized before wavelet analysis.

A key measurement issue in this study is that continuous and comparable monthly data on physical climate disaster severity, epidemiological burden, and actual AI deployment in specific governance systems are difficult to obtain for the full sample period. Therefore, this study uses observable proxy variables. These variables should be interpreted as sustainability-related governance and market signals rather than direct measures of physical risk levels or actual AI governance effectiveness.

First, AI-sector development (AI) is measured using the CSI Artificial Intelligence Index (930713). The index consists of 50 listed companies in China's Shanghai and Shenzhen stock markets that are engaged in AI infrastructure support, technological development, and application services. It captures the capital-market performance and market valuation of AI-related firms in China. However, this index should not be interpreted as a direct measure of actual AI deployment in climate governance or public health governance systems. It may also reflect investor expectations, policy attention, and broader industry cycles.

Second, climate-related government response (CGR) is measured using the Government Response to Climate Risk Index from the ISETS database. This index is constructed from 222,923 entries collected from the official Leadership Message Board between 2011 and 2023 and covers nine categories of climate-related events: heavy rainfall, hailstorms, low temperatures, droughts, heatwaves, lightning, sandstorms, typhoons, and haze pollution. In this study, the index is interpreted as a proxy for government response intensity and institutional attention to climate-related events. It should not be regarded as a direct measure of physical climate disaster severity. A higher index value indicates stronger government response and attention, but it may also reflect improved reporting capacity, stronger administrative responsiveness, or greater public concern.

Third, infectious disease-related market attention (IDA) is measured using a news-based index following Baker et al. [51]. The index tracks stock-market attention and volatility associated with infectious disease outbreaks and incorporates keywords such as epidemic, pandemic, virus, flu, disease, coronavirus, SARS, H5N1, and H1N1. In this study, the index is interpreted as a proxy for market and media sensitivity to infectious disease-related shocks. It does not directly measure epidemiological burden, such as confirmed cases, deaths, hospitalization rates, or disease transmission intensity. Accordingly, a decline in this index indicates lower market and media attention to infectious disease-related shocks, but it should not be directly interpreted as improved public health governance or reduced infectious disease risk.

Finally, the World Uncertainty Index (WUI) is introduced as a control variable. WUI captures broad global uncertainty shocks that may simultaneously influence AI-sector development and risk-related governance signals. Controlling for WUI helps reduce the influence of common global uncertainty, but it cannot eliminate all potential sources of omitted-variable bias, such as domestic industrial policy, digital infrastructure development, macroeconomic conditions, environmental regulation, or public health capacity.

4.3. Descriptive Statistics

Descriptive statistics for all variables are reported in Table 1. The mean values of the four variables are 2696.67 for AI, 0.68 for CGR, 164.29 for IDA, and 4.44 for WUI. The standard deviations indicate that IDA and WUI display relatively strong volatility, while CGR is more stable over the sample period. The skewness results show that CGR, IDA, and WUI are positively skewed, whereas AI is slightly negatively skewed. In terms of kurtosis, IDA and WUI exhibit heavy-tailed distributions, suggesting that they are more sensitive to extreme observations. The Jarque–Bera test results indicate that CGR, IDA, and WUI significantly deviate from normality, while AI does not show a significant departure from a normal distribution.

Table 1. Descriptive statistics of AI, CGR, IDA and WUI.

	AI	**CGR**	**IDA**	**WUI**
Observations	132	132	132	132
Mean	2696.67	0.68	164.29	4.44
Median	2731.88	0.68	17.85	3
Maximum	4765.23	0.77	1556.68	27
Minimum	1017.75	0.55	2.84	0
Standard Deviation	707.78	0.05	255.27	3.94
Skewness	−0.35	0.32	2.29	2.05
Kurtosis	2.97	2.24	10.05	10.36
Jarque–Bera	2.71	5.434 *	389.53 ***	391.01 ***

Note: AI denotes AI-sector development; CGR denotes climate-related government response; IDA denotes infectious disease-related market attention; WUI denotes the World Uncertainty Index. * and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5. Empirical Results

This section reports the results of the continuous wavelet transform and partial wavelet coherence analyses. The red regions enclosed by black contours indicate statistically significant coherence at the 5% level based on 500 Monte Carlo simulations. According to the color scale, warmer colors indicate stronger coherence, whereas cooler colors indicate weaker coherence. All analyses control for the World Uncertainty Index (WUI) to reduce the influence of common global uncertainty shocks.

Several interpretation boundaries should be clarified before discussing the results. First, the reported patterns should be interpreted as time–frequency co-movement and phase-based temporal precedence rather than structural causality. Second, the analysis focuses primarily on statistically significant regions outside, or clearly away from, the cone of influence. Third, given the 132 monthly observations in the sample, evidence in the 4–8 year frequency band is treated as exploratory and interpreted with caution. Finally, climate-related government response (CGR) and infectious disease-related market attention (IDA) are treated as observable sustainability-related risk signals, rather than direct measures of physical climate disaster severity or epidemiological burden.

5.1. AI-Sector Development and Climate-Related Government Response

Figure 1 presents the partial wavelet coherence between AI-sector development and climate-related government response (CGR), as well as the corresponding phase-difference results. Overall, the figure shows a positive and statistically significant time–frequency association between AI and CGR in several periods. However, the phase relationships vary across time and frequency bands, suggesting that the role of AI in the climate-response domain changed over the sample period.

During 2015–2016, a significant coherence region appears mainly in the medium-term frequency band of 2–4 years. The phase difference is concentrated within the interval ($[-\pi/2, 0]$), indicating that CGR positively precedes AI-sector development. This pattern suggests a reactive relationship: stronger climate-related government response and institutional attention were followed by movements in the AI sector. In substantive terms, this result is consistent with the possibility that heightened climate-related events and governance demand increased policy and market attention to AI-related monitoring, prediction, and emergency-management applications. Contextual events during this period, including severe haze episodes and extreme weather events, may provide background for understanding why climate-related response signals became more salient. However, these events should be regarded as contextual interpretation rather than direct causal evidence.

After 2020, the relationship changes in the short-term frequency band of 1–2 years. During 2020–2021 and 2022–2023, the phase difference is mainly located within the interval ($[0, \pi/2]$), indicating that AI-sector development positively precedes CGR. This pattern is consistent with the gradual embedding of AI-related capacity into anticipatory climate governance. As AI applications expanded in fields such as meteorological forecasting, air-quality prediction, disaster warning, carbon monitoring, and energy-system optimization, AI-sector movements may have become more closely linked to forward-looking climate-response capacity. Nevertheless, this finding should not be interpreted as evidence that AI directly reduced physical climate risks. It only indicates that, in the observed time–frequency regions, AI-sector development preceded changes in the climate-related government response signal.

Taken together, the AI–CGR results suggest a shift from a reactive pattern in the mid-2010s to a more anticipatory pattern after 2020. In the earlier period, climate-related response signals preceded AI-sector movements, whereas in the later period AI-sector development preceded climate-response signals in short-term bands. This evolution supports the dual-role perspective of AI in sustainability governance: AI may initially respond to risk-related governance demand, but under certain conditions it may also become increasingly associated with forward-looking governance preparedness.

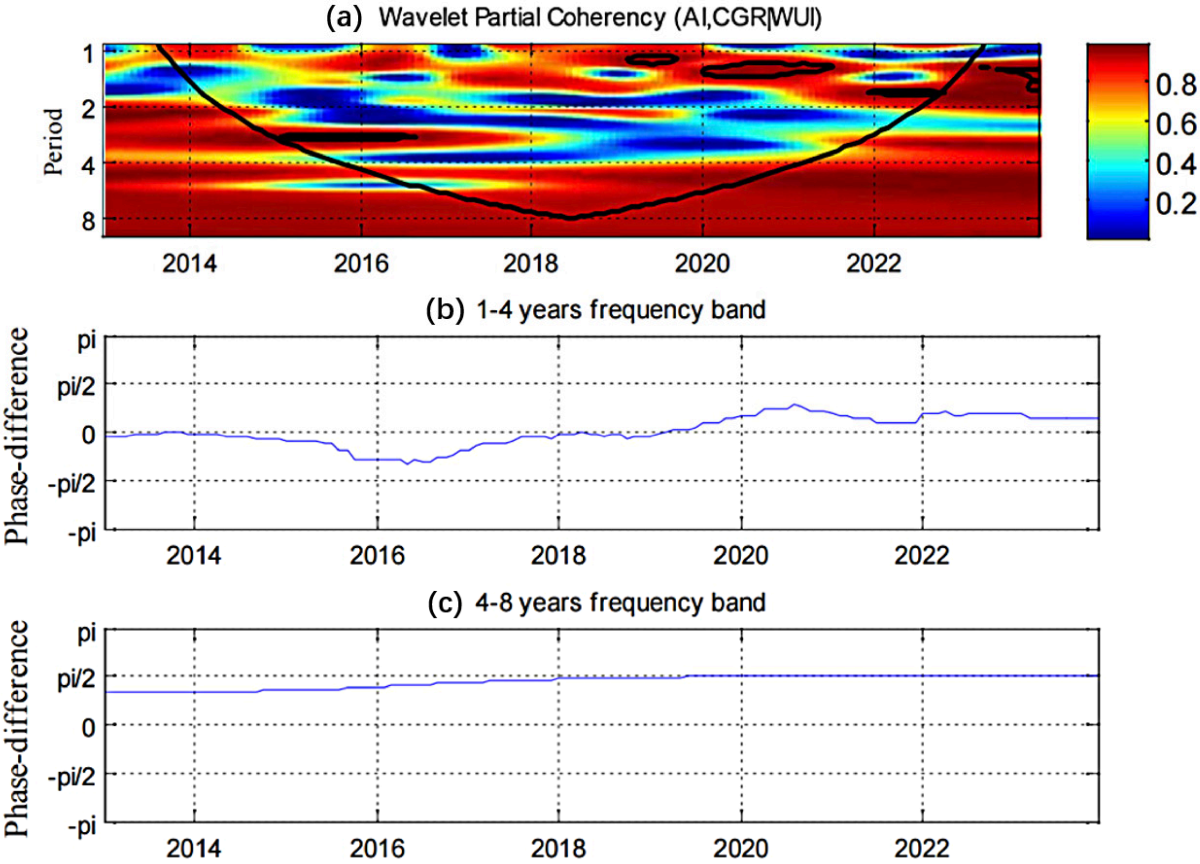

Figure 1. Partial wavelet coherence and phase difference between AI-sector development (AI) and climate-related government response (CGR), with the World Uncertainty Index (WUI) as a control variable. Panel (**a**) shows the coherence results, while Panels (**b**,**c**) display the corresponding phase differences. Regions significant at the 5% level (based on 500Monte Carlo simulations) are enclosed by black contours. The cone of influence (COI) indicates areas potentially affected by edge effects.

5.2. AI-Sector Development and Infectious Disease-Related Market Attention

Figure 2 presents the partial wavelet coherence between AI-sector development and infectious disease-related market attention (IDA), together with the corresponding phase-difference results. The results show significant positive coherence between AI and IDA in several periods, but the phase patterns differ from those observed in the climate-response domain. In particular, the significant regions are mainly characterized by IDA preceding AI-sector development, indicating a more reactive role of AI in public health-related risk contexts.

During 2017–2018, a significant coherence region appears in the medium-term frequency band of 2–4 years. The phase difference is mainly located within the interval ($[-\pi/2, 0]$), suggesting that infectious disease-related market attention positively precedes AI-sector development. This pattern indicates that heightened attention to infectious disease-related shocks was followed by movements in the AI sector. It is consistent with the view that public health concerns and policy attention may stimulate demand for AI-related applications in disease monitoring, epidemic prediction, and health-data analysis. However, the result should be interpreted as a lead–lag association between IDA and AI-sector development, not as evidence that infectious disease outbreaks directly caused AI innovation.

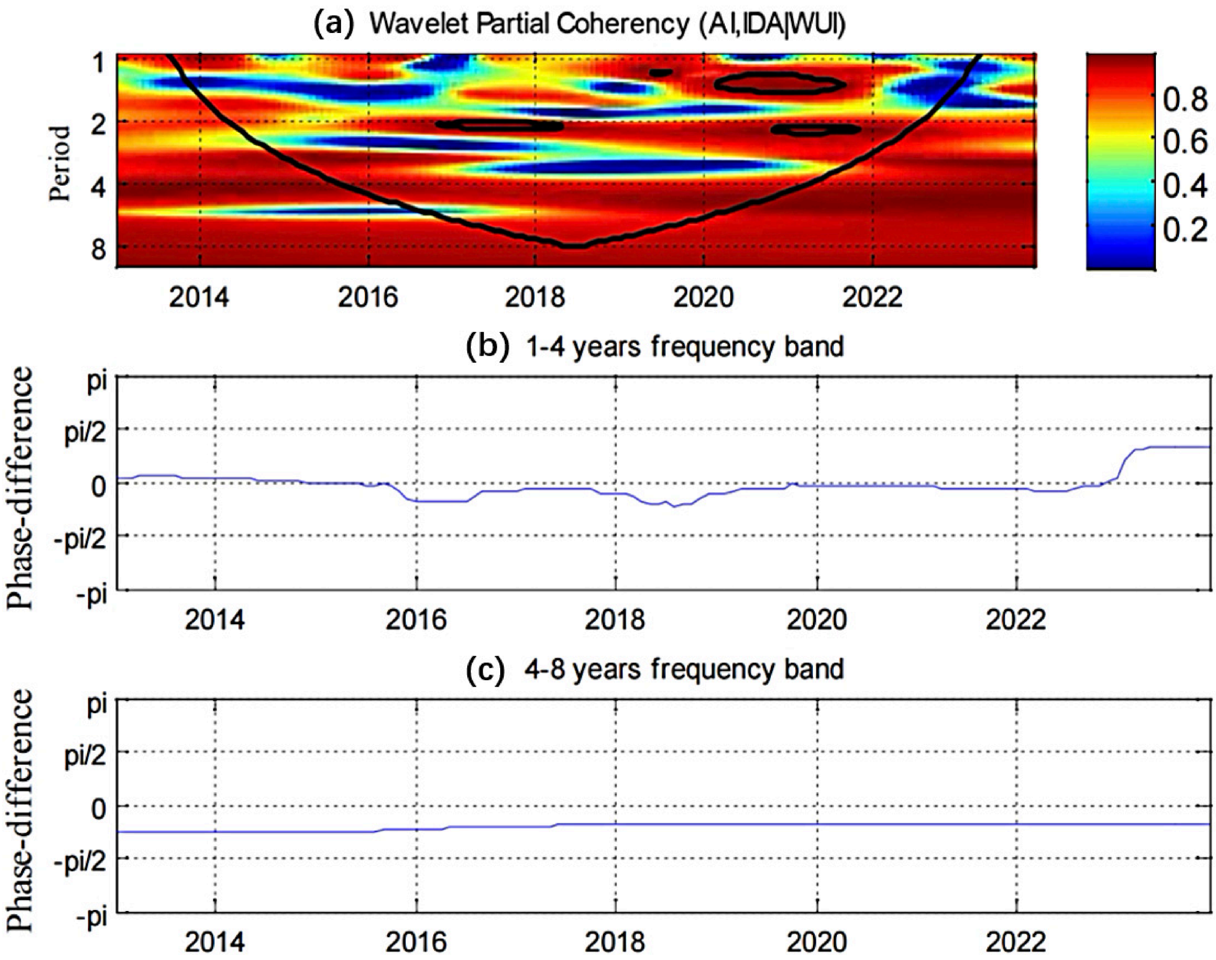

Figure 2. Partial wavelet coherence and phase difference between AI-sector development (AI) and infectious disease-related market attention (IDA), with the World Uncertainty Index (WUI) as a control variable. Panel (**a**) shows the coherence results, while Panels (**b**,**c**) display the corresponding phase differences. Regions significant at the 5% level (based on 500 Monte Carlo simulations) are enclosed by black contours. The cone of influence (COI) indicates areas potentially affected by edge effects.

A similar reactive pattern is observed during 2020–2021, corresponding to the COVID-19 period. In the short-term frequency band of 1–2 years, IDA again precedes AI-sector development. This result suggests that the sharp increase in infectious disease-related market and media attention was followed by stronger AI-sector movements. During this period, AI applications in public health, including epidemic tracking, diagnostic support, medical-resource allocation, and drug discovery, received considerable policy and market attention. These contextual developments may help explain the observed wavelet pattern. Nevertheless, the wavelet results only identify temporal precedence between IDA and AI-sector development; they do not establish that AI directly improved public health outcomes or reduced epidemiological risk.

Importantly, no robust and statistically significant period is identified in which AI-sector development positively precedes IDA within the main interpreted frequency bands. This does not imply that AI lacks value in public health governance. Rather, within the indicator framework of this study, AI-sector development does not show a stable anticipatory relationship with infectious disease-related market attention. Compared with climate-response governance, public health risk contexts involve greater uncertainty, stronger dependence on institutional coordination, and more complex behavioral and epidemiological dynamics. These features may limit the extent to which AI-sector development appears as a forward-looking signal in the infectious disease domain.

Overall, the AI–IDA results suggest that AI plays a predominantly reactive role in infectious disease-related contexts. Infectious disease-related market attention tends to precede AI-sector movements, especially during 2017–2018 and the COVID-19 period. This pattern contrasts with the later-stage AI-leading pattern observed in the climate-response domain and highlights the heterogeneity of AI's dual role across sustainability-related governance contexts.

5.3. Summary of Phase-Based Lead–Lag Patterns

Table 2 summarizes the main phase-based lead–lag patterns identified in the wavelet analysis. The results reveal clear heterogeneity between the climate-response and infectious disease-attention domains. For CGR, the relationship evolves from a reactive pattern in 2015–2016 to an AI-leading pattern after 2020, suggesting that AI-related capacity may have become increasingly associated with anticipatory climate governance. For IDA, the dominant pattern is reactive: infectious disease-related market attention precedes AI-sector development, particularly during 2017–2018 and 2020–2021. This contrast supports the argument that AI has a dual role in sustainability governance, functioning both as a response to risk-related shocks and, under certain conditions, as a potential contributor to forward-looking governance preparedness.

Table 2. Summary of phase-based lead–lag patterns.

Pair	Main Period	Frequency Band	Phase Pattern	Interpretation
AI–CGR	2015–2016	2–4 years	CGR precedes AI	Pattern consistent with a reactive association between AI-sector development and climate-related government response signals
AI–CGR	2020–2021	1–2 years	AI precedes CGR	Pattern consistent with anticipatory climate governance capacity
AI–CGR	2022–2023	1–2 years	AI precedes CGR	Continued AI-leading pattern in short-term climate-response dynamics
AI–IDA	2017–2018	2–4 years	IDA precedes AI	Pattern consistent with a reactive association between AI-sector development and infectious disease-related market attention
AI–IDA	2020–2021	1–2 years	IDA precedes AI	Crisis-related AI-sector response during the COVID-19 period
AI–IDA	No robust AI-leading region	—	—	No stable anticipatory pattern observed under the present indicator framework

6. Conclusion and Recommendations

6.1. Discussion: Reactive and Anticipatory Roles of AI

This study employs wavelet analysis to examine the dynamic relationships among AI-sector development, climate-related government response, and infectious disease-related market attention in the time–frequency domain from 2013 to 2023. The empirical findings show that AI-sector development is positively associated with both sustainability-related governance and attention signals. However, the temporal roles of AI differ substantially across the two domains.

In the climate-response domain, the relationship between AI-sector development and climate-related government response shows a transition from a reactive pattern to an AI-leading pattern. During 2015–2016, climate-related government response preceded AI-sector development in the medium-term frequency band, suggesting that AI-sector movements followed stronger climate-related institutional attention and governance demand. After 2020, however, AI-sector development preceded climate-related government response in the short-term frequency band. This pattern is consistent with the possibility that AI-related capacity became increasingly embedded in monitoring, early warning, forecasting, and decision-support systems for climate-related governance. Nevertheless, this finding should not be interpreted as causal evidence that AI directly reduced physical climate risks. Rather, it indicates that AI-sector development began to move ahead of climate-response signals in specific time–frequency regions.

In the infectious disease-attention domain, the relationship follows a different pattern. During both 2017–2018 and 2020–2021, infectious disease-related market attention preceded AI-sector development in the main significant regions. This suggests that AI played a predominantly reactive role in public health-related risk contexts. The COVID-19 period further illustrates this reactive pattern, as heightened infectious disease-related attention was followed by stronger AI-sector movements. However, within the present indicator framework, no stable AI-leading pattern was observed for infectious disease-related market attention. This does not imply that AI lacks value in public health governance. Rather, it suggests that AI-sector development did not function as an anticipatory signal for infectious disease-related market attention during the examined period.

The heterogeneous results may be related to differences in risk characteristics and governance conditions. Climate-related governance often relies on relatively continuous data streams, such as meteorological observations, satellite data, emissions monitoring, and energy-system information. These data conditions make it easier for AI to be embedded into forecasting and early-warning systems. By contrast, infectious disease governance involves greater uncertainty related to pathogen mutation, population mobility, medical capacity, public behavior, and cross-sector institutional coordination. These characteristics may make AI applications more likely to appear after risk attention rises, rather than before infectious disease-related shocks become salient.

Taken together, these findings support the dual-role perspective of AI in sustainability governance. AI should not be understood as a universal solution to sustainability-related risks. Instead, its role is domain specific. In some contexts, such as climate-related government response, AI-sector development may gradually become associated with anticipatory governance capacity. In other contexts, such as infectious disease-related market attention, AI may function mainly as a reactive response to heightened risk attention and crisis pressure.

6.2. Policy Implications

The findings provide several policy implications for the integration of AI into sustainability governance.

First, governments should strengthen the institutional integration of AI into climate monitoring, early-warning, and decision-support systems. The AI-leading pattern observed in the climate-response domain suggests that AI-related capacity may be increasingly connected with forward-looking climate governance. Policymakers can support the responsible use of AI in areas such as extreme weather forecasting, flood and drought monitoring, air-quality prediction, carbon-emission tracking, and energy-system optimization. However, AI systems should be embedded within accountable governance frameworks, with human oversight, data-quality control, and transparent decision-making procedures.

Second, policymakers should avoid technological solutionism in public health governance. The reactive pattern observed in the infectious disease–attention domain indicates that AI-sector development tends to follow heightened infectious disease-related market attention rather than precede it. Therefore, AI should be treated as a supporting tool rather than a substitute for public health infrastructure, epidemiological surveillance, medical capacity, institutional coordination, and political decision-making. AI-based tools can contribute to epidemic monitoring, disease prediction, medical-resource allocation, and pathogen tracing, but they must be integrated with robust public health systems and cross-sector governance mechanisms.

Third, risk-induced AI innovation should be guided toward sustainability-oriented applications. Major crises may accelerate AI development, but the direction of technological innovation is not automatically aligned with sustainability goals. AI can support green and low-carbon transitions through applications in renewable-energy integration, smart grids, carbon monitoring, and climate-risk assessment. At the same time, beyond the empirical scope of this study, AI may also be used in ways that intensify resource extraction or increase energy consumption. Governments should therefore use research funding, industrial policy, regulatory standards, and public procurement to guide AI innovation toward climate resilience, public safety, ecological protection, and long-term sustainability.

6.3. Research Limitations and Future Directions

This study has several limitations that should be addressed in future research.

First, the indicators used in this study are proxy variables rather than direct measures of physical risks or actual AI deployment. Climate-related government response captures government attention and institutional response to climate-related events, but it does not directly measure physical climate disaster severity. Infectious disease-related market attention captures market and media sensitivity to infectious disease-related shocks, but it does not directly measure epidemiological burden, such as confirmed cases, mortality, hospitalization, or transmission intensity. Similarly, the CSI Artificial Intelligence Index captures the capital-market performance of AI-related firms, but it does not directly measure the actual deployment of AI technologies in climate governance or public health governance systems. Future research could incorporate official disaster statistics, epidemiological data, AI patent records, public procurement data, infrastructure deployment indicators, and firm-level AI adoption measures when consistent monthly data become available.

Second, although wavelet analysis is useful for identifying localized co-movement and phase-based lead–lag patterns, it does not establish structural causality. The findings should therefore be interpreted as time–frequency associations and temporal precedence patterns rather than causal effects. Future studies may combine wavelet methods with other empirical strategies, such as panel models, event-study designs, regression discontinuity designs, mixed-frequency models, or structural causal models, to strengthen causal inference.

Third, the sample consists of 132 monthly observations from 2013 to 2023. While this sample is suitable for short- and medium-term time–frequency analysis, interpretations of long-cycle dynamics, especially in the 4–8 year frequency band, should be treated as exploratory. Future research with longer time spans could provide more robust evidence on low-frequency dynamics.

Fourth, although this study controls for the World Uncertainty Index, WUI cannot capture all potential confounding factors. Domestic industrial policy, digital infrastructure, environmental regulation, macroeconomic cycles, public health capacity, and broader technological trends may also influence AI-sector development and sustainability-related governance signals. Future research could include additional control variables when comparable high-frequency data are available.

Finally, this study focuses on China. China provides a valuable empirical context because of its rapid AI development and complex sustainability governance challenges. However, the findings may not be directly generalizable to countries with different institutional arrangements, technological capacities, public health systems, or environmental governance structures. Future research could conduct cross-country comparative analysis to examine whether the dual role of AI in sustainability governance varies across institutional contexts.

6.4. Conclusions

This study examines the dual role of artificial intelligence in sustainability governance by analyzing the time–frequency relationships among AI-sector development, climate-related government response, and infectious disease-related market attention in China from 2013 to 2023. Using continuous wavelet transform and partial wavelet coherence analysis, the study identifies localized co-movement and phase-based lead–lag patterns while controlling for the World Uncertainty Index.

The findings show that AI-sector development is positively associated with both climate-related government response and infectious disease-related market attention, but the temporal patterns differ across domains. In the climate-response domain, AI-sector development shifts from a reactive pattern in 2015–2016 to an AI-leading pattern after 2020. This suggests that AI-related capacity may have become increasingly connected with anticipatory climate governance. In the infectious disease–attention domain, infectious disease-related market attention consistently precedes AI-sector development in the main significant regions, especially during 2017–2018 and the COVID-19 period. This indicates that AI played a more reactive role in public health-related risk contexts.

These findings contribute to the literature on AI and sustainability governance by showing that AI does not play a uniform role across risk domains. Rather than assuming that AI automatically improves governance effectiveness or directly reduces risk, this study demonstrates that AI can function both as a response to heightened risk-related attention and as a potential component of forward-looking governance capacity. The results also highlight the importance of distinguishing between physical risk, governance response, market attention, and technological development when evaluating the role of AI in sustainability governance.

At the same time, the findings should be interpreted with caution. The indicators used in this study are proxy variables, and the wavelet approach identifies time–frequency associations rather than structural causality. Therefore, the results do not prove that AI directly reduces physical climate risks or epidemiological burdens. Future research should develop more direct indicators of AI deployment and risk outcomes, combine wavelet analysis with causal identification strategies, and extend the analysis to cross-country settings. Despite these limitations, this study provides evidence that AI's role in sustainability governance is conditional, heterogeneous, and shaped by the characteristics of specific risk domains.

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Data Availability Statement: The data could be found here: https://data.worldbank.org/ (accessed on 25 May 2026).

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Appendix A

Wavelet analysis is a useful method for examining the dynamic relationships among AI-sector development, climate-related government response, and infectious disease-related market attention in both the time and frequency domains. Because the interactions among these variables may vary across different periods and cycle lengths, a step-by-step interpretation of the wavelet results is necessary to improve methodological transparency.

The wavelet approach extends the traditional Fourier transform by allowing relationships between variables to be analyzed simultaneously across time and frequency domains. Unlike Fourier analysis, which mainly provides frequency-domain information, wavelet analysis captures both time-varying and frequency-varying characteristics within localized windows. This makes it particularly suitable for analyzing non-stationary and noisy time series, such as AI-sector development and sustainability-related risk signals.

Wavelet coherency measures the strength of localized co-movement between two variables in the time–frequency domain, while the phase difference is used to identify their lead–lag relationship. In this study, AI denotes AI-sector development, Y denotes a sustainability-related risk signal, and WUI denotes the World Uncertainty Index. Specifically, Y refers either to climate-related government response or to infectious disease-related market attention.

The phase difference between AI and Y, conditional on WUI, is defined as:

$$\phi_{AI,Y|WUI}(\tau,s) = \mathrm{atan2}\Big(\mathrm{Im}\Big[\rho_{AI,Y|WUI}(\tau,s)\Big], \mathrm{Re}\Big[\rho_{AI,Y|WUI}(\tau,s)\Big]\Big)$$

where $\rho_{AI,Y|WUI}(\tau,s)$ denotes the complex partial wavelet coherency between AI and Y after controlling for WUI. $\mathrm{Re}(\cdot)$ and $\mathrm{Im}(\cdot)$ denote the real and imaginary parts, respectively. The phase difference $\phi_{AI,Y|WUI}(\tau,s)$ lies within the interval $[-\pi,\pi]$.

When the phase difference is close to zero, the two variables move in the same direction: $\phi_{AI,Y|WUI}(\tau,s) \approx 0$.

When the phase difference is close to π or $-\pi$, the two variables move in opposite directions: $\phi_{AI,Y|WUI}(\tau,s) \approx \pi \mathrm{or} \phi_{AI,Y|WUI}(\tau,s) \approx -\pi$.

In this study, the phase difference is interpreted as follows.

If $0 < \phi_{AI,Y|WUI}(\tau,s) < \frac{\pi}{2}$, then AI and Y move in the same direction, and AI-sector development positively precedes the sustainability-related risk signal Y. This pattern suggests a relationship consistent with anticipatory governance capacity.

If $-\frac{\pi}{2} < \phi_{AI,Y|WUI}(\tau,s) < 0$, then AI and Y also move in the same direction, but the risk-related signal Y positively precedes AI-sector development. This pattern suggests a reactive relationship in which AI-sector movements follow risk shocks or heightened risk attention.

If $\frac{\pi}{2} < \phi_{AI,Y|WUI}(\tau,s) < \pi$. Or $-\pi < \phi_{AI,Y|WUI}(\tau,s) < -\frac{\pi}{2}$, then the variables move in opposite directions, indicating an anti-phase lead–lag relationship. These anti-phase patterns should be interpreted more cautiously than in-phase lead–lag patterns.

In the wavelet coherence plots, the horizontal axis represents the time period, while the vertical axis represents the frequency or cycle length. The color bar on the right-hand side indicates the strength of coherence at each time–frequency point. Warmer colors indicate stronger coherence, whereas cooler colors indicate weaker coherence. The black contour represents regions that are statistically significant at the 5% level based on Monte Carlo simulations. The cone of influence indicates regions potentially affected by edge effects, and results close to or inside this region should be interpreted with caution.

The empirical analysis proceeds in three steps. First, the time–frequency relationship between AI-sector development and climate-related government response is examined to assess whether AI appears mainly as a reactive response or as a potential anticipatory governance capacity in the climate-response domain. Second, the relationship between AI-sector development and infectious disease-related market attention is analyzed to identify whether AI plays a similar or different role in public health risk contexts. Third, partial wavelet coherency is used to control for the World Uncertainty Index, thereby reducing the influence of common global uncertainty shocks on the observed relationships. These analyses allow this study to compare the dual role of AI in sustainability governance across climate response and infectious disease attention.

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