NEXUS BETWEEN ARTIFICIAL INTELLIGENCE AND RENEWABLE ENERGY GENERATION IN CHINA: THE ROLE OF GREEN FINANCE

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PREFACE

Being degree students of Bachelor of Finance, our academic objectives have always been characterized by an unquenchable thirst for comprehending the intricate mechanisms of global financial dynamics. Meanwhile, enquiring into rising or developed financial products and markets, aiming to discover better financial intellectual, as well as discovering the impact of global trends.

At this point of time, we discovered a trend of global discussion regarding Renewable Energy, that is intended to ensure sustainability. While China is being the leader in addressing this issue, triggering mushrooming discussions around the area. Whilst the integration of Artificial Intelligence in related industry is also crucial to take note.

This cultivates the curiosity of us, on how a financial products or services can exert influence in aiding the progress of sustainable. Screening from thousands of financial products, Green Finance is incorporated into our study due to small market size. We eager to evaluate the impact and role of Green Finance in this area.

After going through a plethora of scholar literature, statistical analyses, and empirical data, we endeavoured to illuminate the role of Green Finance in the Nexus of Artificial Intelligence and Renewable Energy Generation. Armed with financial analysis tools and guided by a rigorous methodological approach, our journey was one of exploration and revelation.

ABSTRACT

The global transition towards renewable energy has gained significant attention in recent years, with China emerging as the biggest producer of renewable energy. However, past research has yet to acknowledge the significance of artificial intelligence on advancing the renewable energy generation. This paper discusses the significance of artificial intelligence in facilitating renewable energy generation and the mediating and moderating role of green finance based on China annual data from 1992-2021. This research incorporated Autoregressive Distribute Lag Model (ARDL) to examine for the existence of mediating and moderating role of green finance in the long run and synergistic effect of green finance and artificial intelligence. This study highlights the following key finding. First, there is long run relationship between green finance on the relationship between artificial intelligence and renewable energy generation. Second, green finance has a partial mediating effect of green finance on the relationship between artificial intelligence and renewable energy generation. Third, green finance plays an effective moderating roles in the nexus between artificial intelligence and renewable energy generation. These findings inspire us to propose policy implications for China should strength its position in the renewable energy generation through promoting green finance and integrating artificial intelligence.

Keywords: Artificial Intelligence, Renewable energy generation, Green finance, China, ARDL

Area: HD9502-9502.5 Energy industries. Energy policy

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LIST OF ABBREVIATIONS

%	Percentage
A(t)	Technological progress
AI	Artificial intelligence
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
C	Capital
CES	Constant Elasticity of Substitution
CO_2	Carbon dioxide emissions
CSRC	China Securities Regulatory Commission
DL	Distributed Lag
E	Environmental sustainability
Eq.	Equation
ESG	Environmental, social, and governance
ETS	Emissions Trading System
EVs	Electric vehicles
FDI	Foreign direct investment
GDP	Gross domestic product
GF	Green finance
GW	Gigawatts
IEA	International Energy Agency
IoT	Internet of things
IT	Information technology
IV-GMM	Instrumental Variables-Generalized Method of Moments
JB	Jarque-Bera
KPSS	Kwiatkowski-Philips-Schmist-Shin Test
L	Labour
LCB	Lower Critical Bound
LM	Lagrange Multiplier

OLS	Ordinary least squares
OWID	Our World in Data
PP	Phillips-Perron Test
REG	Renewable energy generation
RMB	Renminbi
TFP	Total Factor Productivity
TWh	Terawatt hours
UCB	Upper Critical Bound
UECM	Unrestricted error correction model
US	United States
WEF	World Economic Forum
Y	Output

CHAPTER 1 RESEARCH OVERVIEW

1.0 Research Background

Climate change remain one of the most pressing global challenges, primally driven by rising greenhouse gas emission, particularly carbon dioxide emission (Khan et al., 2021; Zhao et al., 2022d). These consequence of climate change have led to catastrophic outcomes on the sustainability of ecosystems and humans (Bidwell & Sovacool, 2023; Zhao et al., 2022a). In 2024, the global temperatures reached the highest level on record in 175 years of observation, above the pre-industrial average (1850-1900) by around 1.5°C (World Meteorological Organization, 2025). This temperature increase largely correlates with the global carbon dioxide emission record high of 37.41 billion tonnes (Gt) in 2024, over 60% higher since 1990.

In response to the climate crisis, numerous nations have recognised the need of mitigating climate change; the development of renewable energy is a key strategy (Naeem et al., 2023; Taghizadeh-Hesary et al., 2023). Since adopting the Paris Agreement in 2016, 196 countries at the UN Climate Change have been forced to limit the earth's temperature to above pre-industrial levels by limiting greenhouse gas emissions before 2025 and declining 43% by 2030. Global Clean energy skyrocketed in 2023, and renewable increased by 50% with 507 gigawatts compared to 2022, with solar photovoltaic accounts for three-quarters of the addition (International Energy Agency [IEA], 2024b).

In addition, the European Union and 130 other national government committed together to quadruple the installed renewable energy capacity globally to at least 11,000 GW by 2030 (IEA, 2024). Based on this expansion, it is anticipated that more than 17,000 terawatt hours (TWh) of energy would be generated globally from renewable sources by 2030. This sum is sufficient to meet China's and the US's combined electricity needs in 2030 (Bojek, 2025).

The energy industry uses a significant portion of green financing in green transition to support sustainable development (Bai et al., 2022). Investors are increasingly drawn to green financial products and derivatives due to their promising future return, which is driving a surge in trade (Sangiorgi & Schopohl, 2021; Zhao et al., 2022). Meanwhile, as the globe transition towards the era of intelligence, innovations such as renewable energy robotics to Artificial Intelligence (AI) unleash opportunities to drive the global green transition to renewable energy. Research on artificial intelligence has shown that AI can enhance environmental, economic, and social aspects. According to recent studies, the application of industrial robot in the development of AI technology can lessen carbon emissions, improve trade product quality, and encourage green innovation and inequality between developing and developed nations, (Li et al., 2022; Wang et al., 2023b; Yu et al., 2023). Furthermore, integration of AI has big potential to increase renewable energy generation given its significant correlation with and technological advancement and energy efficiency.

However, for renewable energy technologies to scale effectively, robust financial development is important. Green finance facilitates environmentally friendly projects by supporting investments in renewable energy projects and issuing financial products like green credit and green bonds (Nguyen et al., 2021; Wang & Zhao, 2022). By funding sustainable infrastructure, and renewable energy technology, green finance play a crucial role in mitigating transition and physical climate hazards (Arfaoui et al., 2024). Hence, it is important to examine the role of green finance in bridging the gap between artificial intelligence and renewable energy generation in China.

1.1 China Background on Renewable Energy Development

China has emerged as the global leader in renewable energy investment, committing $818 billion and its equivalent to two-thirds of $2.1 trillion globally, making it a global powerhouse in clean energy generation. This dominance reflects China’s goal to achieve carbon neutrality before 2060 aims and peak CO_2 emissions before 2030; propelling enormous renewable energy infrastructure at a speed that outpaces all other countries. Additionally, the Chinese government provides investment to fund research that increases expenditure by 70% between 2018 and 2023. These efforts have fuelled the broad adoption of green technologies from electric vehicles (EVs) are identified using green license plates to vast solar panels run for kilometres (Chan, 2025).

As the largest contributor to global renewable energy, China accounted for 50% of global renewable installation in 2023, primarily driven by its aggressive expansion of solar and wind capacity (IEA, 2024). China built solar photovoltaic capacity in 2022 that was equivalent to entire world’s capacity. In 2023, it nearly quadrupled its energy storage, doubled new solar installations, and increased new wind capacity by 66%, (Hilton, 2024). These rapid expansion made China to surpass its target of 1,200 gigawatts of solar and wind power by 2030 in 2024, reaching this milestone 6 years ahead of schedule. Meanwhile, China's solar capacity grew by 45.2% (277 GW), while wind capacity increased by 18% (80 GW). Contributing to a 14.6% increase in overall energy generation mainly driven by renewables. This results from aggressive investments, government policies, and a surge in solar and wind installation (Jennifer, 2025).

This rapid green transition has not only strengthened China's domestic energy security but also positioned China as a global leader in renewable energy innovation. From visible worldwide from Sichuan Province to Zimbabwe; China is creating a global sustainable development roadmap, actively shaping the future of renewable energy in combating climate change. Within this dynamic environment, AI has become the new driver in the green transition, driving innovation in renewable energy production and enhancing efficiency management systems in China (Chan, 2025).

1.2 Problem Statement

The climate issue remains critical, although China's renewable energy has been widely adopted and developed. Since 2006 China remain the biggest emitter of greenhouse gases, with coal consumption 30% more than the world combined, roses to 8.77 billion tonnes in 2024 (Jeniffer, 2025; Greenfield, 2024; Liu et al., 2023). In 2022, China's coal consumption is approximately 50% of the world combined and forecasted to maintain until 2026 (IEA, 2023). Vast contribution of CO_2 emissions that originate from burning of fossil fuels such as coal, oil and natural gas to generate electricity or power vehicles and machines (Hausfather & Friedlingstein, 2022). In 2023, renewable energy will account for 35% of the electricity mix, while 65% of fossil fuel for non-renewable energy (Yang & Zhang, 2024).

Numerous studies acknowledge the catalytic role of AI technologies in propelling renewable energy development. AI solves all engineering issues and strengthens energy systems' operations, especially in the electricity market (Xu et al., 2019). By incorporating AI, it speeds up transition to clean energy few AI-driven solutions through smart grid integration, advanced forecasting, and energy storage optimisation that stabilise and fortify the energy system while increase predictability of renewable energy source. However, problems with data accessibility, system compatibility, and privacy must be fixed in order to fully utilise AI's potential. Thus, China need to reduce its dependence on fossil fuels by leveraging AI as a catalyst for energy transition to contribute to global climate goals, and achieve a net-zero future (Qiang et al., 2025).

Despite China's policy to drive renewable energy development through integrating AI and Climate Finance, renewable energy development has not kept pace. This is because in AI adoption, IT companies have made limited progress in transitioning to renewables (Chen, 2024). Forecasts predict a 160% rise in China's data centre demand, leading to a 152% increase in carbon emissions (Xue, 2024). In AI adoption, China's energy sector faces challenges such as inconsistency in the regulatory framework, cybersecurity risks, and data privacy concerns (International Association for Energy Economics, 2024; Rhodes, 2020). Besides, high computational demands and complex algorithms further hinder integration. Furthermore, supply unpredictability is caused by technical problems such as expensive equipment and restricted measuring coverage (Liu, 2024). These factors deter investment in AI-driven renewable solutions due to high costs, long innovation cycles, and uncertain returns. Green finance is essential to addressing future sustainable development needs since it improves the stability, affordability, and dependability of renewable energy (Gayen et al., 2024). However, China incentives favour brown investments, such as "clean coal" (Chen et al., 2024; Cubric, 2020; Matschoss et al., 2019). Thus, China's green finance market remains small, with limited financial instruments and restricted funds for renewable energy (Green Finance & Development Centre, 2023, 2024).

China's outstanding advancements of deploying renewable energy and the big potential of AI-driven solutions is limit by China strong reliance on fossil fuels and AI's inability to be fully integrated into renewable energy. This shows existing financial procedures undervalue the significance of green financing in bridging these gaps and favour conventional energy investments over AI-driven renewable projects (Zhao et al., 2024). Therefore, this study investigates the role of green finance in closing the gaps between AI and renewable energy generation towards achieving China's long-term climate commitment and promote a more sustainable energy transition.

1.3 Research Objectives

1.3.1 General Objectives

This research aims to examine the role of green finance in the relationship between artificial intelligence and renewable energy generation in China.

1.3.2 Specific Objectives

1. To examine whether green finance plays the role of moderator in influencing the nexus between artificial intelligence and renewable energy generation in China.

2. To examine whether green finance plays the role of mediator in influencing the nexus between artificial intelligence and renewable energy generation in China.

1.4 Research Questions

1. Does green finance moderate the nexus between artificial intelligence and renewable energy generation in China?

2. Does green finance mediate the nexus between artificial intelligence and renewable energy generation in China?

1.5 Hypothesis of the Study

1.5.1 Moderating Role

H_0: Green finance does not moderate the nexus between artificial intelligence and renewable energy generation in China.

H_1: Green finance moderates the nexus between artificial intelligence and renewable energy generation in China.

1.5.2 Mediating Role

H_0: Green finance does not mediate the nexus between artificial intelligence and renewable energy generation in China.

H_1: Green finance mediates the nexus between artificial intelligence and renewable energy generation in China.

1.6 Significance of Study

From the research background and the issues around the world, there is a notable opportunity where the integration of AI, green finance and renewable energy generation can solve the global sustainability issue. If significant progress in AI is achieved, it is expected to strengthen the capacity of renewable energy generation by improving energy efficiency, predicting energy systems and increasing the control of the smart grid. This significant progress has recently become increasingly notable. Still, the effectiveness of green finance, which provides the necessary funding and risk management tools, and its accessibility are critical to successfully integrating AI into renewable energy. Hence, examining the moderating and mediating role of green finance in this research is important as it shows whether the green finance system can enhance or impede the influence of AI on renewable energy generation. This research can serve as a reference for the stakeholders and government as it can provide future strategies to guide the development of renewable energy and consider the economy and environment as priorities.

A clear understanding of how green finance can moderate the relationship between AI and renewable energy generation is expected to bring critical benefits to the Chinese government. Policymakers are more likely to create more effective measures to magnify the positive impacts of AI on renewable energy projects, while addressing limitation such as high costs and technological uncertainty by anticipating how policy interventions and regulatory frameworks, such as tax incentives, subsidies, and green investment licenses, will affect this relationship. It is expected that this knowledge will improve the government's ability to coordinate national and international initiatives in line with climate goals (e.g., net-zero emission targets). In addition, the government should be able to work with investors, businesses, and communities to promote large-scale sustainable development by recognizing the moderating role of green finance. It is expected that China's financial system will be optimally structured to support AI-integrated renewable energy infrastructure by prioritizing these regulatory levers, paving the way for a more sustainable and resilient energy future.

In addition, the mediation role of green finance in influencing the nexus between AI and renewable energy generation in China is expected to benefit other stakeholders, including investors, businesses, and communities, and to successfully drive and support technological breakthroughs in the renewable energy industry. If green finance carries a mediation role, it will emphasise how financial systems enhance the integration of AI in renewable energy projects, which can ultimately affect the feasibility and scalability of such projects. Shareholders are often more exposed to higher costs and technological risk when involved in AI-driven renewable energy solutions. In this case, green finance, which includes green bonds, sustainable loans and venture capital, can provide immediate funding and reduce the financial risk. Understanding green finance's role as a mediator is expected to help stakeholders identify the most effective financial instruments to support the integration of AI, optimise resource allocation, and align their investments with environmental, social, and governance (ESG) objectives. This knowledge might enable them to make informed decisions that balance profitability and sustainability, ensuring long-term value creation while contributing to global climate goals.

CHAPTER 2 LITERATURE REVIEW

2.0 Introduction

In this chapter, this research will look into the key concepts integral to this research, such as green finance's moderating and mediating role. In addition, this research provides the theoretical framework and identify the research gap.

2.1 Empirical Study

In recent decades, research has shown a trend towards AI's impact on society, similar to that of the renewable energy sector. Further research was done to study the direct relationship of AI towards renewable energy generation. Most of the findings have proven a positive effect between the nexuses. Li et al. (2023) studied the positive direct effect of AI by integration of robots, which can effectively increase the productivity of renewable energy; Ukoba et al. (2024) have proven that continuously advancing AI contributes to opportunities to increase efficiency and optimizing the grid while fostering integration in the renewable energy system. A similar conclusion was made by Manuel et al. (2024) that it can help increase the energy system's longevity and reliability. Wang et al. (2023b) further the research by expanding the area into less developed and industrialized regions in China; Zhao et al. (2024) focus on the regions that have lower levels of renewable energy development and found that there is a profound effect when AI is adopted. Even with the integration of AI, it can create a positive impact on high-quality energy development, and this finding has further strengthened the importance of AI in that industry (Wang et al., 2024).

Other than studying its impact, AI has been proven to optimize production, with a research showing that AI can effectively contribute to the industry by playing an assistance role (rather than human-only and AI-only) in helping technical inspectors with predictive maintenance (Shin et al., 2021). It can also contribute to increment in the optimization of production via AI predictions, analysis models (supporting vast amounts of data), improved energy storage solutions, and smart grid management systems (Hamdan et al., 2024).

In addition, Rasheed et al. (2024) also figured out AI's mutual relationship with renewable energy in China and other developing Asian countries using a panel asymmetric causality test. This further expands the possibility of AI in renewable energy. Up until now, it has been proven that by integrating AI, efficiency and productivity can substantially increase by reducing the costs of renewable energy technology, and most of the research tells that AI works on renewable energy predominantly via their technology and innovation effect (Zhang et al., 2022; Bennagi et al., 2024).

Furthermore, financial instruments were also invented along the way, in line with the attention paid to the environment and clean energy. For example, green finance was introduced as a financial service for economic activities that support environment improvement, climate change mitigation and more efficient resource utilization (The People's Bank of China, 2016). While it becomes more adaptive to the Paris Agreement and Sustainable Development Goals (Berrou et al., 2019). Therefore, studying how green finance can contribute to renewable energy generation is also important. Several studies showed that green finance significantly promotes renewable energy generation (Zhao et al, 2024; Tang & Zhou, 2023). For example, green finance provides the required financial resources to aid the deployment and advance of renewable energy projects. (Aquilas and Atemnkeng, 2022; Alharbi et al, 2023).

Besides, it helps to cover the initial investment costs of renewable energy by providing grants and loans; green finance minimizes the financial barrier and makes renewable energy projects more economically feasible and attractive to investors (Jin et al., 2021; Lee et al., 2022; Qi et al.,2023). It also provided theoretical evidence that green bonds can facilitate the deployment of green energy and reduce carbon emissions through sufficient financial resources (Rasoulinezhad & Taghizadeh-Hesary, 2022). To conclude, green finance enhances the renewable energy sectors by providing a mature financial instrument for funding those renewable energy projects.

However, research in the USA finds evidence for the non-linear impact of green finance on renewable energy using the m-QQR model ranging monthly data from 1985-2020 (Sinha et al., 2023). Hence, it is crucial to understand and study more than just the impact of green finance in improving renewable energy generation. This research also aims to study the moderating role of green finance in conjunction with the relationship between current AI technologies and renewable energy generation.

In recent years, there have been extensive literature point out the role of green finance between the relationship of AI and renewable energy generation. In 2022, the study found that FinTech innovation will enhance green credit and investment in China, resulting in economic growth (Zhou et al., 2022). This established the first-ever interaction between fintech and green investment, which tends to bring positive insight into economic development. After that, when the global target slowly shifted to integrating AI and renewable energy, green finance started to interact with AI (Lee et al., 2023; Xiong & Dai, 2023). Instead of using green investment and green finance, Zhao et al. (2024) decided to use the proxy of climate finance to examine its moderating role (using the IV-GMM approach) in the nexus between AI and renewable energy in 2000-2019. Most of these past studies supported this theory and suggested that the interaction between AI and green finance can increase renewable energy generation. Therefore, Chinese industry players must clarify its role to welcome sufficient funding for AI innovation and further enhance the renewable energy generation system.

Other than looking at the moderating role of green finance, government should also pay attention on the mediating role to further strengthen the impact achieve by AI in the renewable energy generation. At this point of time, finance plays an important role while there is a surge of financing and credit creation in AI and renewable energy. Hence, China’s government needs to examine the role of green finance to further the diffusion of AI and gradually increase renewable energy generation. A study was made to examine the mechanism of green finance in encouraging the flow of funds into renewable energy sectors. The finding by Ramzani et al. (2024) further explained the mechanism of AI-powered green finance using the ANOVA test. AI also increases the capability of dealing with risk assessments, finding investment opportunities, and even facilitating resource allocation. Information-driven decision-making methods also enhance environmental and financial sustainability (Shajar et al., 2024).

This is true when Chen et al. (2024) find a positive impact (significant spatial spillover effect) of green finance on AI innovation in China. Furthermore, it has been proven that the green finance pilot policy can help promote progress in AI adoption and innovation in China. Ultimately, this growth in green finance and AI can lead to the development of renewable energy generation (Li et al., 2022). It established a positive relationship that green finance posed on AI and renewable energy (Bilal & Shaheen, 2023). Another study in China expanded the role of green finance in promoting renewable energy by integrating AI with Fintech and has proven that higher innovation in

Fintech could increase the efficiency of green finance, facilitating renewable energy financing (Sadiq et al., 2023). Therefore, this research aims to examine the mediating and moderation role of green finance in aiding AI in achieving a higher level of renewable energy generation in China.

2.2 Theoretical Study

2.2.1 Cobb Douglas Production Function

Cobb Douglas Production Function is a production theory that measures the amount of production in manufacturing by considering the changes in the amount of labour and capital. It was initially used to examine the relationship between labour (L), capital (C) and output (Y) in U.S. manufacturing. According to empirical studies, the output elasticity of capital and labour are found to remain relatively stable, supporting the idea that production could be represented in the function of Y =AKαLβ, where A is total factor productivity (TFP), and α and β represent the proportion of output contributed by capital and labour, respectively (Douglas & Cobb, 1928). As this model can represent real-world production accurately, especially in sectors with constant returns to scale ($\alpha + \beta = 1$), it has been widely accepted. However, later studies have challenged this model regarding its assumption of stable substitution elasticity and applicability across different industries (Felipe & Fisher, 2003). Although this model has a few limitations, the Cobb-Douglas function remains the basis for both macroeconomic and microeconomic production research. At the same time, it still significantly impacts the following factors: productivity estimation and growth theory's advancement (Humphrey, 1997; Felipe, 2014).

The original Cobb-Douglas function could explain the short-term variation effectively, but it failed to consider the long-run economic growth. Due to this limitation, the Cobb-Douglas function was extended by incorporating technological progress A (t) as the increment factor in sustained productivity. Empirical studies from Solow uncover that capital accumulation alone cannot explain long-term growth effectively. This is because the diminishing returns to capital reflect the increase in C, leading to a smaller addition to Y (Solow, 1956). To solve this issue, Solow has introduced technological progress and modified the function to $Y = A(t)C\alpha L\beta$, where A(t) grows over time due to innovations and efficiency improvements (Mankiw, Romer, & Weil, 1992). The function modified by Solow has reshaped the macroeconomic growth theory, emphasising that total factor productivity (TFP) will be the primary source of sustained economic expansion. Cross-country growth comparison then validates this modified function (Barro & Sala-i-Martin, 2004). However, there is still criticism mentioning that this function treats technology separately, and this criticism has led to changes in the late 20th century (Romer, 1986).

Other than the drawbacks and limitations mentioned above, another major criticism of the Cobb-Douglas function was that it assumes the unitary elasticity of substitution, which $\sigma = 1$. This represents that labour and capital are the substitutions of each other in fixed proportions. Due to this criticism, the Constant Elasticity of Substitution (CES) production function was introduced to address this issue. The CES production function incorporates a variable elasticity of substitution parameter (σ) that allows the industries with different capital-labour relationships to be modelled more accurately (Arrow et al., 1961). Empirical research also found that capital-labour substitutability and labour-capital ratios vary among different industries, which contradicts the rigid constraints of the Cobb-Douglas function (Felipe & McCombie, 2014). Since the CES production function has addressed the issue incorporated in the Cobb-Douglas function, it has become a more useful tool to model production in industries that have different input flexibility and is being used widely to grow and develop the economy (Acemoglu, 2009; de La Grandville, 1997).

CES still has its limitation, which is incorporating functional restriction on the relationship between input, although it has enhanced flexibility by providing variable elasticity substitution. Hence, this limitation leads to introducing the Translog (Transcendental Logarithmic) production function to address this issue by offering a second-order approximation of any general production function (Christensen, Jorgenson, & Lau, 1973). The empirical findings of Griffin, Montgomery, and Rister proved that the production inputs always have a nonlinear interaction. This means that the return to scale and substitution will have different effects across industries and time periods (Griffin, Montgomery, & Rister, 1987). In order to make the function to be more applicable in complex industries such as energy, technology, and finance, the Translog function incorporated the interaction term between capital, labour, energy, and other inputs (Berndt & Christensen, 1973). The modified function was then widely used in analysing productivity, cost structures, and technological changes in various economies (Hulten, 2001).

Except for the finding of Solow emphasising that technological progress drives long-term growth, endogenous growth models were introduced by incorporating human capital and research development (R&D) investment as production factors into the production function (Romer, 1986; Lucas, 1988). Empirical research has proved an increasing growth rate in the economy's investment in education, knowledge creation and R&D. Hence, this led to the further development of the Cobb-Douglas framework into $Y = AC\alpha L\beta H\gamma$, where H represents the accumulation of human capital and knowledge spillovers (Aghion & Howitt, 1998). The endogenous growth models criticised technological progress as both exogenous and economic decisions and policies driving it. The government could actively facilitate development via education subsidies, intellectual property protection, and innovation policies (Mankiw, Romer, & Weil, 1992). This resulted in a focus on capital accumulation and knowledge-driven growth, which became instrumental in explaining why some nations grow faster than others (Barro, 1991).

Researchers have recently modified the Cobb-Douglas function by including the ecological and technological factors due to the growing concern about climate change, environmental sustainability and artificial intelligence. Due to this, the Green Cobb-Douglas production function was introduced. This function includes environmental sustainability (E) and AI-driven productivity (AI) as key inputs and extends the traditional Cobb-Douglas function (Zhang & Da, 2020). Empirical studies on China's industry sector also proved that the production function can be improved if carbon emissions, renewable energy adoption, and machine learning innovations are integrated into the production function (Zeng, Wang, & Yu, 2021). The modified function expressed as Y = ACαLβEγAIδ shows that the digital transformation and climate policies in economic production have become more important (Brynjolfsson & McAfee, 2014). Since businesses and policymakers emphasise carbon neutrality and AI-driven efficiency, this application ensures that economic models align with 21st-century technological and environmental challenges (Acemoglu & Restrepo, 2018).

2.2.2 Techno-economic Paradigm

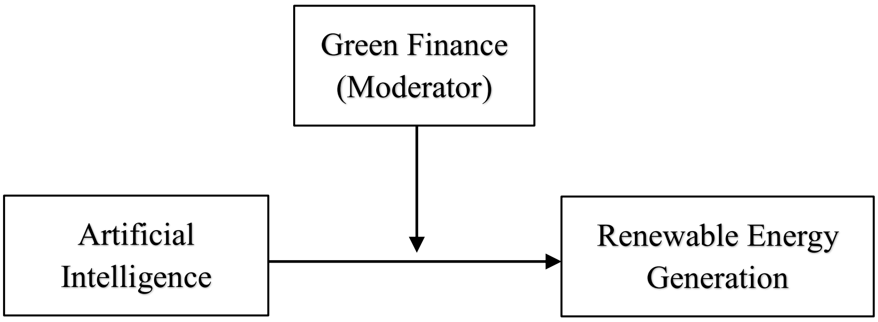
The techno-economic paradigm originated from Schumpeter in the 19th century, which initiated the application of technical change and entrepreneurship at the root of economic growth (Perez, 2009). Perez then uses this idea to form the Techno-economic paradigms, which explain several revolution levels since the Industrial Revolution. The new techno-economic paradigm will be initiated when an innovation breaks through the old version and starts to increase deployment (Drechsler et al., 2009). In the late 19th century, it was mentioned that there was potential for the sixth Paradigm to rise, where renewable energies provide an energy system (Freeman, 1999). The new revolutions always come with the opportunity to shift to low-cost input, which could also effectively increase the speed and reliability of the new products (Perez, 2009). The new Paradigm is driven by the technology surge (AI) associated with renewable energies, where investments become increasingly intense, and the falling costs start to impact market expansion (Mathews, 2012).

The discussion was made to determine the possibility of AI being deployed as the new technological Paradigm that could replace the old inventions such as IoT. Further research was made to study their patenting activities and applicants, pointing out that there is an obvious increment in the adaption and diffusion of AI innovation, forming a new paradigm (Giacomo et al., 2024). This new paradigm encourages further studies to look into the new mechanism in the decade that could increase the effectiveness of the production of renewable energies and the utilization of AI. This is closely connected to the government's future policy efforts to promote further AI breakthroughs in accelerating its energy transition (Zhang et al., 2024). Government support has become an extremely important element in fulfilling the transition of the new Paradigm and eventually achieving the objective of promoting renewable energy (Tian et al., 2024). Therefore, it is more than crucial for the China’s government to seize the golden investment opportunities to bring the new wave in renewable energy sectors.

2.3 Theoretical Framework

Mediating Role

Moderating Role



2.4 Literature Gap

While it is evident from the above discussions that the relationship between renewable energy generation, AI, and green finance has drawn significant attention from scholars, there remain substantial gaps in the existing literature.

One of the key reference studies in this field examines climate finance as the independent variable and identifies its mediating and moderating role in the relationship between AI and renewable energy. However, climate finance represents only one component of green finance. It does not fully capture the broader scope of green finance, which includes sustainable investments, green bonds, and environmental risk management. As a result, the role of green finance as a whole in the relationship between AI and REG remains unverified. This research aims to address this gap by examining green finance, providing a more comprehensive understanding of its role in AI and REG.

Second, there is extensive research on the relationships between AI and renewable energy generation, as well as green finance and renewable energy. However, studies that integrate all three variables, AI, green finance, and renewable energy generation, within a single framework remain limited. Most existing research focuses on only two of these components, leaving a gap in understanding how green finance mediates or moderates the relationship between AI and renewable energy generation. Hence, this research aims to close this gap by examining the role of green finance on renewable energy generation and AI to provide a more comprehensive study of their relationship.

CHAPTER 3 METHODOLOGY

3.0 Introduction

This chapter mainly focuses on the research methodology used to examine the role of green finance in the relationship between AI and renewable energy generation in China. The first section provides a data description defining all variables and their source. Then, the chapter outlines the main step in data processing procedures, from the unit root test to the ARDL approach. Finally, the chapter shows the diagnostic checks conducted.

3.1 Data Description

China's renewable energy generation (REG) is retrieved from Our World in Data (OWID). Renewable energy is a broad term that includes hydropower, wind energy, solar energy, biomass, and heat pumps (Ahmed et al., 2022). Hence, this research uses the total hydropower, wind, solar, and other renewables, including China's bioenergy, as the proxy for renewable energy generation. The unit measurement for this variable is terawatt-hours.

AI is still an emerging technology; it is difficult to determine its actual level of development and size because of its active involvement in many different sectors and applications. Some studies measure AI from the perspective of technology innovation, such as the total number of patents related to AI (Wang et al., 2023a; Zhang et al., 2023). Hence, this research decided to use the number of patent applications and residents as the proxy of AI in China. The data is retrieved from the World Bank. On the other hand, completed investment in industrial pollution treatment represents the proxy to measure the green finance (GF) in China. This proxy is measured in millions of RMB. This data was retrieved from CEIC Data.

Regarding control variables, there are two variables: foreign direct investment (FDI) and carbon dioxide emissions (CO_2). Both are measured in the percentage of GDP, where the proxy of foreign direct investment is the net inflow from the balance of payment in current US$. At the same time, carbon dioxide emissions use the kiloton of carbon dioxide as a proxy. Both data are retrieved from the World Bank. This research has incorporated FDI as our control variable because, to ascertain the effect of AI in China, FDI is the most important element in facilitating additional funds flow from other techno-country. It is also the medium through which the transfer of technology could happen by bringing new technology into China. Investment in China can bring more innovation and enhancement in the renewable energy sectors, especially in wind and solar generators, potentially increasing production efficiency. As the main objective of shifting towards renewable energy started from the vision to achieve net zero emissions, this research would like to keep it as a control variable, looking at its impact towards renewable energy generation. It is important because CO_2 emissions are the key indicator to measure environmental sustainability. It is also crucial for us to see whether or how the changes in CO_2 emissions will affect China's decisions and policy implications in promoting integration in AI and renewable energy generation. However, omitting important variables is still possible in studying green finance's role in China. Hence, future studies need to be enhanced by taking into account more accurate variables to ensure the robustness of further studies.

The data incorporated in this research are quantitative and comprise 30 time-series observations from 1992 to 2021. Data descriptions for all variables are incorporated in **Table 3.1**.

Table 3.1

Source of Date for Variables

Type of variable	Variables	Proxy	Unit of measurement	Sources of method
Dependent Variable	Renewable Energy Generation (REG)	Total hydropower, wind, solar, and other renewables, including China's bioenergy	terawatt-hours (TWh)	Our World in Data (OWID)
Independent Variable	Artificial Intelligence (AI)	Number of patent applications and residents	Unit	World Bank
	Green Finance (GF)	Completed investment in industrial pollution treatment	millions of RMB	CEIC Data
Control Variable	Carbon Dioxide Emissions (CO_2)	Kiloton of carbon dioxide	% of GDP	World Bank
	Foreign Direct Investment (FDI)	Net inflow from the balance of payment in current US$	% of GDP	World Bank

3.2 Unit Root Test

3.2.1 Phillips-Perron Test (PP)

The preliminary test must be done before running the bound test and ARDL. This research applies the Phillips-Perron (PP) unit root test to test order integration in time series analysis. This research also applies

Newey-West Bandwidth as the default bandwidth and Bartell kernel as the spectral estimation method. To avoid spurious regression results and biased parameter estimation, a unit root confirms whether the variables are differenced appropriately to achieve stationarity at a level of integration I (0) or I (1) and not higher to minimise the risk. ARDL cannot accommodate variables integrated in the order I (2) or I (3). PP unit root null hypothesis represents that a time series is integrated into the order or unit root. The alternative hypothesis represents that there is no unit root or stationery. Not rejecting the null hypothesis indicates that the time series is unit root and non-stationary, meaning the data mean and variance can change over time (Phillips & Perron, 1988). It must be ensured that the dependent variable (REG) is significant at the first difference level to carry out the ARDL long-run bound test.

$$\Delta REG_t = \alpha + \beta_t + \gamma lnY_{t-1} + \sum_{i=1}^{p} \delta_i \Delta lnREG_{t\ t-1} + \epsilon_t$$

Where:

ΔREG_t = First difference for Renewable Energy Generation (REG) in natural logarithmic form at a particular time.

ΔREG_{t-1} = First difference for Renewable Energy Generation (REG) in a natural logarithmic form at a preceding time

$\beta_t = Time\ trend$

α = Intercept

t = Intercept and trend

ϵ_t = Error term

3.2.2 Kwiatkowski-Philips-Schmist-Shin Test (KPSS)

Besides, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationary test is used to test the stationarity of the variables, and both have opposite null hypotheses of stationarity. This research also applies Newey-West Bandwidth as the default bandwidth and Bartell kernel as the spectral estimation method. The KPSS null hypothesis represents the series with no unit root or stationary. Alternate hypotheses represent that there is a unit root or non-stationary as PP tests only test for a random walk or unit root, while KPSS tests for a random walk or unit root cover non-stationary without the root. Thus, cross-checking the results using PP and KPSS allows us to achieve consistency and reliability of the stationarity. This provides stronger evidence for the data properties of variables are either I (0) or I (1), but not I (2).

$$REG_t = \mu + B_t + r_t + \epsilon_t$$

Where:

μ = intercept

B_t= Time trend

r_t = random walk

ϵ_t = stationary error term

3.3 Model Specification

$$LREG_t = \beta_0 + \beta_1 LAI_t + \sum_{t=1}^{n} \beta_k \, control_t + \varepsilon_t \qquad \text{Eq. (1)}$$

$$LGF_t = \gamma_0 + \gamma_1 LAI_t + \sum_{t=1}^{n} \gamma_k \, control_t + \varepsilon_t \qquad \text{Eq. (2)}$$

$$LREG_t = \delta_0 + \delta_1 LAI_t + \delta_2 LGF_t + \sum_{t=1}^{n} \delta_k \, control_t + \varepsilon_t \qquad \text{Eq. (3)}$$

$$LREG_t = \lambda_0 + \lambda_1 LAI_t . LGF_t + \sum_{t=1}^{n} \lambda_k \, control_t + \varepsilon_t \qquad \text{Eq. (4)}$$

$LREG_t$ denotes the natural logarithmic value of renewable energy generation (TWh) at time t. LAI_t denotes the natural logarithmic value of artificial intelligence (unit patent application) at time t. LGF_t denotes the natural logarithmic value of green finance at time t. $LAI_t.LGF_t$ denotes the natural logarithmic value of the multiplication of artificial intelligence and green finance. While $control_t$ denotes the natural logarithmic value of control variables at time t, which included FDI (% of GDP) and Carbon Dioxide Emission (% of GDP). ε_t denotes disturbance term at time t. In this research, all variables are converted into the logarithm form to stabilize the variance and reduce the impact of extreme values. This can ensure that our results are more robust and accurately estimated.

Several models need to be formed to tackle the role of GF in the nexus between AI and REG. Firstly, a baseline regression represents the nexus between the dependent and core variables. The baseline regression model is derived based on the underlying Cobb-Douglas Production as above.

Secondly, in order to examine the mediating role of GF in the nexus between AI and REG, regression models are formed in Eq. (2) and (3) based on Eq. (1). Before the research can identify the existence of mediating role, it is important to examine the relationship between AI and GF as regressed in Eq. (2), as well as the relationship between GF, AI, and REG as regressed in Eq. (3). The mediating role of GF is only established when both of the models result in significant effect.

Eq. (2) was formed as the relationship between AI and green finance must be examined, and a significant relationship must be shown to proceed to equation 3. Extensive research examines the mediating role of some, of them using AI as an independent variable and some using it as a dependent variable. However, in this research, Eq. (2) was trying to examine the effect of AI on green finance. This is because the environmental, social and governance (ESG) analysis can be enhanced using AI. It can quickly process massive amounts of ESG data to assess sustainability performance. AI can also assist in detecting greenwashing and ensure that all green financing is directed to the resources that can be utilised most efficiently. Besides, AI can also enhance risk assessment and prediction by analysing climate risk factors and assessing their impact on finances. Machine learning can estimate the default risk in a green project by considering unconventional data sources. Third, a green investment portfolio can also be optimised through algorithms driven by AI, which can provide suggestions on sustainable investment opportunities by analysing renewable energy, carbon credit, and ESG-compliant firms' trends. In addition, AI can also automate carbon footprint tracking and reporting. Some AI tools can monitor the carbon emission of every company, supply chain and investment portfolio. Integrating AI, like blockchain technology, can also strengthen the transparency of carbon credit trading and ensure compliance with climate policies. China's government leverages AI in ESG compliance monitoring and carbon trading systems to drive green finance. The China Securities Regulatory Commission (CSRC) and other regulatory bodies use AI-powered tools to analyse corporate sustainability reports and detect greenwashing, ensuring companies provide accurate ESG disclosures (Clifford Chance, 2024). Meanwhile, AI is critical in China's Emissions Trading System (ETS), as it automates carbon credit verification and optimises pricing mechanisms. AI-powered sensors and IoT devices help track companies' real-time carbon emissions, ensuring compliance with China's dual carbon targets (peak carbon emissions by 2030 and carbon neutrality by 2060) while reducing fraud in carbon credit trading (International Carbon Action Partnership [ICAP], 2024).

Lastly, GF's moderating role is examined by forming a new regression model, as stated in Eq. (4). This model incorporates an interaction term by multiplying AI and GF ($LAI_t.LGF_t$). This enables the research to examine the indirect impact of GF to REG via interaction with AI.

3.4 ARDL Approach

3.4.1 ARDL Bounds Test

Once the variables are in either I(0) or I(1), this research will employ a bounds test to determine if there is cointegration between dependent and independent variables or between independent variables. There are three reasons for using this instead of the classical integration test. First, this approach can be used regardless of whether the variables are I (0) or I(1). Secondly, this test can derive an unrestricted error correction model (UECM) through a simple linear transformation. Thirdly, the empirical results of this approach are superior as they provide consistent results for a small sample (Pesaran et al., 2001). Rejecting the null hypothesis indicates a cointegration or long-run relationship between variables. The null hypothesis and its alternative for the equation can be stated as:

$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ (There is no long-run level relationship)

$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$ (There is long-run level relationship)

3.4.2 ARDL

The Autoregressive Distributed Lag Model (ARDL) estimates the long and short-run relationships between different time series variables using ordinary least squares (OLS) regression. Besides, the Autoregressive (AR) captures the short-term relationship fluctuations between variables and represents the dependent variable's lagged values. For explanatory variables, the lagged values are represented by Distributed Lag (DL) components, which capture the lagged effects of the independent variables on the dependent variable (Pesaran et al., 2001).

Since the research sample size is small, used Narayan's (2005) Lower Critical Bound (LCB) and Upper Critical Bound (UCB) is being used to compare the computed test statistic value. The null hypothesis of no long-run relationship is rejected when the F statistic exceeds the UCB; this concludes there is a long-run relationship. The null hypothesis is not rejected if the F test statistic is below LCB. The test will be inconclusive if the F test statistic falls between the two bounds (Narayan, 2005).

After cointegration is formed, the second step will be obtaining the long-run and short-run models based on the following tentative models for ARDL level relation [shown as Eq. (6)]. Restriction to two lines with parsimony are imposed on the ARDL specification order (p,q,r,s,v) in the level of variable ($LREG_t$, LAI_t, $LFDI_t$, $LCO2_t$). In this research, lag length of 1 is chosen.

$$\begin{aligned} LREG_t = \theta_0 &+ \sum_{i=1}^{p} \theta_{1,i} LREG_{t-1} + \sum_{i=0}^{q} \theta_{2,i}\colon LAI_t \\ &+ \sum_{i=0}^{r} \theta_{3,i} LGF_t \\ &+ \sum_{i=0}^{s} \theta_{4,i} LFDI_t + \sum_{i=0}^{v} \theta_{5,i} LCO2_t + \varepsilon_t \quad \text{Eq. (5)} \end{aligned}$$

The long run parameters are derived by using Eq. (6) to Eq. (10):

Long-run elasticity for natural logarithmic value of Renewable Energy Generation:

$$\omega_0 = \frac{\theta_0}{1 - \sum_{i=1}^{p} \theta_{1,i}} \qquad \text{Eq. (6)}$$

Long-run elasticity for the natural logarithmic value of Artificial Intelligence:

$$\omega_1 = \frac{\sum_{i=0}^{q} \theta_{2,1}}{1 - \sum_{i=1}^{p} \theta_{1,i}} \qquad \text{Eq. (7)}$$

Long-run elasticity for the natural logarithmic value of Green Finance:

$$\omega_2 = \frac{\sum_{i=0}^{r} \theta_{3,1}}{1 - \sum_{i=1}^{p} \theta_{1,i}} \qquad \text{Eq. (8)}$$

Long-run elasticity for the natural logarithmic value of Foreign Direct Investment:

$$\omega_3 = \frac{\sum_{i=0}^{s} \theta_{4,1}}{1 - \sum_{i=1}^{p} \theta_{1,i}} \qquad \text{Eq. (9)}$$

Long-run elasticity for the natural logarithmic value of Carbon Dioxide Emissions:

$$\omega_4 = \frac{\sum_{i=0}^{v} \theta_{4,1}}{1 - \sum_{i=1}^{p} \theta_{1,i}} \qquad \text{Eq. (10)}$$

The result of the choice of ARDL specification (*p,q,r,s,v*) specification, the long-run elasticity model of LAI_t , $LGF_t, LFDI_t, LCO2_t$ (ω_1, ω_2, ω_3, ω_4) is stated as Eq. (11):

$$LREG_t = \omega_0 + \omega_1 LAI_t + \omega_2 LGF_t + \omega_3 LFDI_t + \omega_4 CO2_t + \varepsilon_t \qquad \text{Eq. (11)}$$

After securing the long-run relation, the error-correction model (ECM) in the first difference that is associated with the long-run estimates is specified as Eq. (12):

$$\Delta LREG_t = \theta_0 - \left(1 - \sum_{i=1}^{p} \theta_{1,i}\right) ECT_{t-1} + \sum_{i=1}^{p} \theta_{1,i} \Delta LREG_{t-1} + \sum_{i=0}^{q} \theta_{2,i} \Delta LAI_{t-i} + \sum_{i=0}^{r} \theta_{3,i} \Delta LGF_{t-i} + \sum_{i=0}^{s} \theta_{4,i} \Delta LFDI_{t-i} + \sum_{i=0}^{v} \theta_{5,i} \Delta LCO2_{t-i} + \varepsilon_t \qquad \text{Eq. (12)}$$

All the ARDL steps need to be repeated for all regression models stated in the previous part, including Eq. (1), (2), (3), and (4). Results must be obtained so that all the models can examine the mediating and moderating role using the ARDL approach.

Lastly, in order to ensure that the models and results are out of diagnostic problems, several diagnostic checks were done, such as (1) the Jarque-Bera (JB) test, as proposed by Jarque & Bera (1980), to check the normality of the models. (2) Autoregressive Conditional Heteroskedasticity (ARCH) test, as proposed by Engle (1982), to tackle conditional heteroskedasticity in time series analysis. (3) Lagrange Multiplier (LM) test, as proposed by Breusch & Pagan (1980), to ascertain the existence of serial correlation in time series analysis. At this level, it ensures our model is normally distributed, achieves homoscedasticity, and is autocorrelation-free. In addition, CUSUM/CUSUM of square test were carried out for the detection of shifts in the mean or intercept term and to detect changes in variance or volatility of time series data. It helped this research to detect structural breaks within time.

CHAPTER 4 RESULT DISCUSSION

4.0 Introduction

This chapter will explore the role of green finance in the relationship between AI and renewable energy generation in China. To achieve this, this research employs ARDL method to generate the result and analyse the outcome to get conclusive findings. This discussion aims to provide valuable insights for this research endeavours.

4.1 Descriptive Statistics

Table 4.1

Descriptive statistics

	Renewable Energy Generation	Artificial Intelligence	Green Finance	Foreign Direct Investment	Carbon Dioxide Emission
Mean	6.2679	11.7301	10.2950	1.1474	1.3320
Maximum	7.8033	14.1708	11.5106	1.8224	1.3512
Minimum	4.8747	9.2114	8.4217	0.2706	1.2902
Standard deviation	0.9292	1.8543	0.8566	0.4280	0.0187
Skewness	0.1619	-0.0432	-0.5681	-0.5780	-1.0151
Kurtosis	1.6223	1.4721	2.1987	2.3907	2.5444
Observations	30	30	30	30	30

Table 4.1 shows the descriptive statistics of the dependent and independent variables used in this research. AI, green finance, foreign direct investment and carbon dioxide emission have a negative skewness, whereas only renewable energy generation appears negatively skewed. This can result from a greater mean than the

renewable energy generation data median. Next, the statistics also reveal that all variables have positive kurtosis. Positive kurtosis indicates that the variables have more extreme values than they would be under normal distribution. Hence, there would be a higher probability of extreme events.

Table 4.2

Result of Phillips-Perron Unit Root Test

	Level		First Difference	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
REG	0.5834(8)	-1.9698(4)	-6.5583(0)***	-6.7676(3)***
AI	-0.3972(4)	-1.8170(4)	-3.5247(3)**	-3.4468(3)*
GF	0.0920(0)*	0.9888(3)	-	0.0122(3)**
CO_2	-1.1817(2)***	-2.1276(2)***	-	-
FDI	-1.3826(2)	-4.3961(3)***	-7.7795(1)***	-
AI.GF	0.4287(3)	0.9982(2)	0.0112(3)**	0.0214(3)**

***, **, and * indicate that the null hypothesis of a series has a unit root is rejected by 1%, 5%, and 10% significance level, respectively.

Table 4.3

Result of Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Stationary Test

	Level		First Difference	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
REG	0.7061(4)**	0.1374(4)*	0.1675(6)	0.1226(9)
AI	0.6873(4)**	0.1026(4)	0.1627(4)	-
GF	0.6191(4)	0.1938(3)**	-	0.0759(3)
CO_2	0.6786(4)**	0.1039(4)	0.1477 (2)	-
FDI	0.5540(4)	0.1454(3)*	-	0.0872 (2)
AI.GF	0.6795(4)**	0.1428(4)*	0.3352(2)	0.1380(3)

***, **, and * indicate that the null hypothesis of a series has stationarity is rejected by 1%, 5%, and 10% significance level, respectively.

Table 4.2 results show that GF and FDI intercepts have stationarity in level form. While REG, AI, CO_2 and AI.GF intercepts only have stationary in first difference. For trend and intercept, only AI and CO_2 have stationarity in level form. Whereas REG, GF, FDI and AI.GF have stationary. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was conducted to enhance the results of this research.

The results in **Table 4.3** show that all variables perform stationary in the intercept of level form. However, AI and CO_2 turn into non-stationary regarding trend and intercept. In the result for the first difference, only CO_2 shows a constant non-stationary result in intercept and trend and intercept. REG, AI and AI.GF turns stationary while GF and FDI turn non-stationary when intercept changes to trend and intercept. Therefore, with stationarity and non-stationarity in level and first differencing form, this research will carry forward the long-run bound and cointegration test.

4.2 Bound Test

Table 4.4

Result of bound test for cointegration analysis

		Eq. (1)	Eq. (2)	Eq. (3)	Eq. (4)
ECT_{-1}	Coeff.	-0.2334	-0.0908	-0.2963	-0.1035
	T-stat	8.6840***	10.0508***	8.8921***	8.0624***

***, **, and * indicate statistical significance level at 1%, 5%, and 10%, respectively.
All T-stat are in negative(-) form.

By using the autoregressive distributed lag (ARDL) model, bound cointegration is tested. **Table 4.4** represents the result of Error Correction Model. In the model, the Error Correction Term (ECT) of all variables was performed at a negative value and fell between 0 and 1, while all of the equations performed significantly at a 1% level. It indicates that the deviations from the long-run equilibrium are corrected over time in the short run. At the same time, a larger absolute value of the ECT represents a faster correction to the equilibrium. As of the results in Table 4, ECT of Eq.(3) is the fastest among Eq.(1) and Eq.(3), which have the respective ECT of 0.2334 Eq.(1), 0.2963 Eq.(3), and 0.1035 Eq.(4). This means that when green finance is used as a mechanism to foster the impact of AI in promoting renewable energy generation, it takes less time to adjust back to the equilibrium. Thus, the government must consider the efficiency and effectiveness of relevant renewable energy policies. Besides that, the government may also consider the technology barriers and financial constraints in facilitating the implementation of the new policy.

Table 4.5

Results for long run model

Long run elasticity				
Variables	Eq. (1)	Eq. (2)	Eq. (3)	Eq. (4)
	REG	GF	REG	REG
AI.GF				0.3782**
AI	0.4995***	0.4031***	0.5502***	
CO_2	-0.1659	2.1000	-0.1452	-0.7060
FDI	0.0271**	-0.0654	0.0036**	0.3377**
GF			-0.1501	
REG				
Constant	0.3952	0.5152	1.3327	-2.9428
F-statistic	12.9279***	9.3173***	10.8250***	11.1433***
Obs.	30	30	30	30
Diagnostic Checking				
LM	4.7706** (0.0394)	0.5135 (0.4808)	2.1660 (0.1559)	2.0491 (0.1670)
ARCH	0.0539 (0.8183)	0.0937 (0.7620)	0.0805 (0.7789)	0.1174 (0.7346)
JB	0.0913 (0.9553)	0.9991 (0.6068)	0.3150 (0.8543)	1.1175 (0.5719)
RESET	3.3086* (0.0820)	2.0112 (0.1695)	1.5815 (0.2224)	5.0554 (0.0354)

***, **, and * indicate statistical significance level at 1%, 5%, and 10%, respectively.
Diag. check: ***, **, and * indicate rejection of null hypothesis at 1%, 5%, and 10%, respectively.
Values within parenthesis denote p values.
LM: Lagrange multiplier; ARCH: Autoregressive conditional heteroscedasticity; JB: Jarque-Bera: RESET: Ramsey specification error test

In **Table 4.5**, both mediating Eq. (2) & (3) column and moderating Eq. (4) column show favourable results for this research in examining the long-run relationship of our model. Eq. (2) and Eq. (3) incorporate the mediating role of green finance in the relationship between AI and renewable energy generation. The result in Eq. (2) column shows a significant relationship between AI and green finance, in which a 1% increase in green finance will contribute to a 2.0679% increase in AI at a 1% significance level. This result can be explained by the fact that AI can quickly process and analyse massive amounts of data. Hence, financial institutions can use AI in their decision-making process as AI enhances data accuracy and risk and reward management (Nepal et al., 2025). In the Eq. (3) column, the result also shows a significant relationship between AI and renewable energy generation: a 1% increase in AI will lead to 0.4800% of renewable energy generation at a 1% significance level. At the same time, the overall model result is significant at 1%, which confirming that the variables can jointly explain the variation in the renewable energy generation. AI enhances the flow of funds in green finance. With proper financing distribution, funds can be directed to the renewable energy sector and improve renewable energy generation in several ways, such as by enhancing the technology used. Through the support of AI, green financing can be optimised to achieve the transition to renewable energy. The optimisation can be achieved through the advances in energy grid efficiency through AI predictive analytics. This assists in financial institutions' evaluation and finance of renewable energy projects that can increase renewable energy generation.

By leveraging AI, green finance becomes more efficient, transparent, and data-driven, ultimately accelerating the shift toward an increase in renewable energy generation. However, the result of green finance is barely satisfactory, because the effect is negative and insignificant. With 1% increase in green finance, renewable energy generation will decrease by 0.1501%. It explained that green finance, being a mediator does not significantly transmit effect onto renewable energy generation.

However, it shows that there is a significant relationship between the moderating effect of GF in the nexus of AI and Renewable Energy Generation in Eq. (4) column. A finding from Zhao et al. (2024) has also revealed a similar result by establishing moderation role of climate finance in nexus of AI and renewable energy generation. When green finance interacts with AI, it could significantly contribute to renewable energy generation in China with a considerable effect of 0.3782%, which is stated in Eq. (4) column. Green finance plays an important role as a medium to increase the flow of funds into China while inviting technology transfer into China that could enhance the effectiveness of renewable energy generation (Gu et al., 2022; Tawney & Weischer, 2021). Green finance and AI interaction can stimulate renewable energy generation in China more effectively.

Notably, the result shows that CO_2 emission will hurt renewable energy generation. This is reasonable as a result of climate change. It is less efficient in generating renewable energy due to unpredictable changes and disruptions in regional weather. The result also indicates that when the performance of AI is weakened, CO_2 emissions are more likely to have a greater negative impact on renewable energy generation and vice versa. It has further proven that renewable energy generation sectors need AI to predict climate change and regional weather more accurately to ensure higher efficiency in renewable energy generation.

Figure 4.1 CUSUM test Eq. (1)

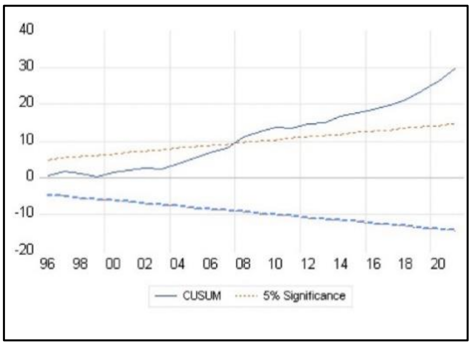


Figure 4.2 CUSUM test Eq. (2)

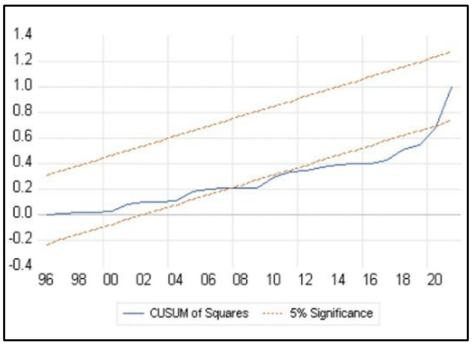


Figure 4.3 CUSUM test Eq. (3)

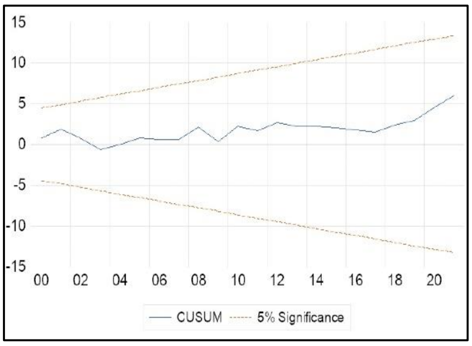


Figure 4.4 CUSUM test Eq. (4)

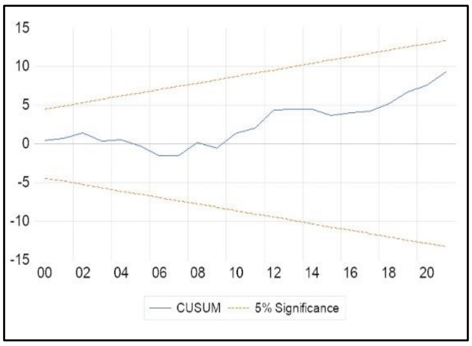


Figure 4.5 CUSUM Square test Eq. (1)

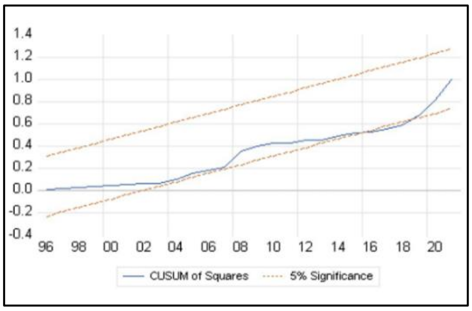


Figure 4.6 CUSUM Square test Eq. (2)

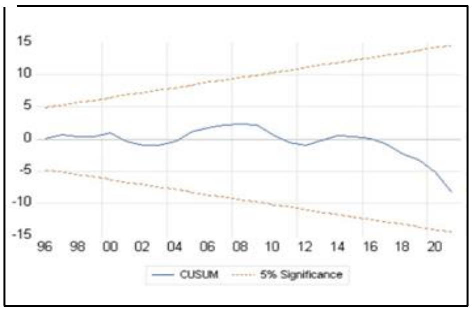


Figure 4.7 CUSUM Square test Eq. (3)

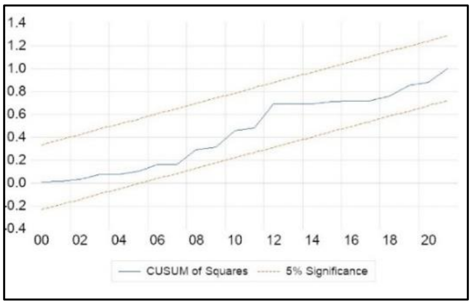


Figure 4.8 CUSUM Square test Eq. (4)

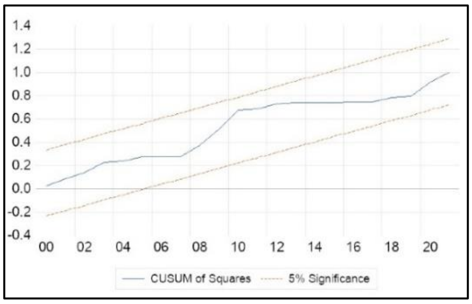


Table 4.5 also presented diagnostic testing for the models. Breusch-Godfrey serial correlation LM test is used to test the existence of autocorrelation in the model. In all models, the test statistic indicates no rejection of the null hypothesis. Hence, there is no autocorrelation. ARCH test tests the existence of heteroscedasticity in the error term. The model is homoscedastic because test statistic does not reject the null hypothesis. Moreover, the Jarque-Bera test is used to test the normality of the error term and the results showed that null hypothesis is not rejected and concludes that the model is normally distributed. Lastly, the Ramsey RESET test is used to test the model specification with the results obtained, all model is being correctly specified.

In Figures 4.1, 4.2 and 4.5, it showed the shift in the mean and variance, respectively. This is due to the reason of autoscedasticity. However, the cumulative sum (CUSUM) test in Figures 4.3 and 4.4 indicates no shift in the mean or level of the time series. In contrast, the CUSUM square test in Figures 4.6, 4.7 and 4.8 indicates no changes in the time series' variance and volatility. Hence, the results conclude that the main model Eq. (3) & (4) has no structural instability or break. This would suggest that the result obtained from the model is a reliable estimation of results.

This research finds that green finance plays a significant moderating and mediating role in AI and renewable energy generation, which is aligned with past research in this area. However, it is worth noting that the study used climate finance as their primary proxy, whereas this research focuses on green finance more broadly. While climate finance is a major component of green finance, our approach includes a wider range of financial instruments and strategies to foster environmental sustainability. This broader scope allows our findings to remain consistent with existing literature while expanding the understanding of the dynamics between AI and renewable energy generation. The relationship observed underscores the potential of green finance in driving the transition to a sustainable energy future, particularly when integrated with advanced technologies like AI.

It is also critical to draw attention to the distinctions between the research methodologies employed in this research and those of earlier scholars. The reference study used the Instrumental Variables-Generalized Method of Moments (IV-GMM) approach to examine both short- and long-term effects, providing a comprehensive analysis of the interaction between climate finance, AI, and renewable energy generation. In contrast, this research uses the Autoregressive Distributed Lag (ARDL) model, which is particularly suited for examining long-run relationships. The ARDL method allows us to focus specifically on the long-term impact of green finance on the relationship between AI and renewable energy without making assumptions about short-term fluctuations or dynamics. Our research objective drives this methodological choice to capture the long-term role of green finance between AI and renewable energy generation.

CHAPTER 5 DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Summary

In current decades, promoting renewable energy generation has become an indispensable action plan for all nations. While China being the largest producer of renewable energy must make their lead in increasing the efficiency of energy generation in order to achieve the goal of Carbon Neutrality in 2030. Along with the increasing focus on environmental sustainability, AI is also going through a bounding decade with mushrooming innovation and diffusion. With the introduction of machine learning and AI predictions, it brings convenience as well as higher efficiency to the renewable energy industry. In order to amplify and increase the production of renewable energy, new mechanisms should take place, and in this case, this research intend to look into the effect and role that current financial invention such as green finance can bring into the nexus. Therefore, this research incorporated Autoregressive Distribute Lag Model (ARDL) to tackle for the existence of mediating and moderating role of green finance in the long run, while at the same time examining the synergy effect of green finance and AI. Research has included an observation of 30 years (1992-2021). As the result, green finance has significant effect on both mediating and moderating role in China. This result is meaningful for the China to understand how green finance can help by playing a mediation and moderation role, along with the integration of AI recently.

5.1 Major findings

In our finding, green finance is playing both mediating and moderating role in the nexus between AI and renewable energy generation. Firstly, by bringing advantages to investors that intend to help in promoting China's renewable energy generation. AI is crucial for the investors to make informed decision in investment regarding renewable sectors. This is especially useful for investors such as the renewable energy factory, government and institutional investors. AI technology drives the advancement of green finance by enabling the rapid processing and analysis of vast amounts of data. Financial institutions may use this data to guide their decisions and even obtain more precise risk and reward analyses of green projects by using AI algorithms. AI can improve risk prediction and real-time monitoring, which can assist to reduce financial risks and guarantee transaction security given the complexity of environmental, social, and governance issues in green finance. AI also promotes innovation in environmentally friendly financial products and services. For example, AI-driven insights may be used to create new green bonds, green funds, and other investment products that address the growing demand for sustainable investments. AI also encourages innovation in green financial services and products. For example, AI-driven insights can support the development of new green bonds, green funds, and other investment products that cater to the growing demand for sustainable investments. While the mechanism of green finance plays an important role, by guiding the flow of funds to green projects (including renewable energy generation), whereby providing stimulant on the production. Yet, the effect of this role is not satisfied for further implications for the government. In fact, it contributes negatively to renewable energy generation.

While in sight of moderating role, green finance is playing an important responsibility in amplifying the effect of AI in improving the renewable energy generation. Green finance could be an instrument to initiate fund to the innovation and adoption of AI in generating renewable energy. By encouraging more public investment to green finance and AI, it could gradually increase the efficiency of renewable energy generation. In fact, it can help the industry to moderate the challenges of lacking financial support. This indeed requires the initiative from government to impose relevant instruments or policies to ensure financial viability. For example, China government can impose tax relief policy or tax incentives to the investors or AI companies to encourage long-term investment. This allow the flow of fund being more accurately directed to the renewable energy sectors, by promoting the AI adoption together with new technologies invention. This is true when green finance supports the AI-based smart grids, to enhance the efficiency of energy generation. Green finance plays the crucial role to scale renewable energy solutions, which in turn stabilizing the renewable energy projects and ensure long-term sustainability.

5.2 Policy Implications

The Chinese government can utilize the findings for future policy settings. Since green finance can only carry a partial mediation role to renewable energy generation, our finding should suggest China to focus on the role of moderation, knowing that green finance does more than just funding a projects; it as well enhances the effectiveness of other renewable energy drivers.

First and foremost, government should align green finance with technological advancement. Governments should prioritize green finance policies that support AI-driven renewable energy solutions, such as smart grids, predictive maintenance systems, and energy consumption optimization platforms. Making AI-readiness or digital integration a prerequisite for green financial support ensures that capital is directed toward projects with higher efficiency and innovation potential. With that, government can ensure higher scalability of energy solutions. This policy should be implemented at the preliminary stage, which help in injecting initial capital to the renewable energy sectors.

Next, government can also expand green financial infrastructure. Establishing dedicated green banks or expanding national green bond markets can facilitate easier access to finance for renewable energy projects. These institutions can offer low-interest loans, credit guarantees, or blended finance structures to attract private investors, particularly in early-stage or high-tech renewable energy projects. It required the initiative and synergy between the financial institutions and government to further promote the new instrument to maximize its impact.

Not only that, but government can also foster Public-Private Partnerships, which involve in a collaboration arrangement between China government with private firms to build and operate projects. In this case, government plays an important role to introduce subsidies, tax incentives and fund green bonds; while the firms in the energy sector can supply technology and manage the operation of power plants. Utilizing public green finance, together with the government involvement to co-finance large scale projects (perceived with higher risk), it can provide higher confident to investors, eventually stimulating more investment in renewable energy.

By strategically deploying green finance as a policy lever and amplifier, governments can accelerate renewable energy generation. At the same time, China can reinforce its commitment to carbon neutrality, enhancing its leading position in green finance and AI energy innovation, and support economic growth in long term within a sustainable, low-carbon framework.

5.3 Limitations and Recommendations

This research explores the role of green finance in renewable energy generation and AI in the long run, but it has two key limitations. Firstly. future studies have to extend their focus beyond China to include both emerging and industrialized nations, including the US, Korea, Japan, and others. This extension would assist in overcoming the data availability restrictions of the current research. At the same time, future studies should incorporate more recent datasets beyond 2021 to ensure a more comprehensive and up-to-date understanding of the topic. Secondly, our studies focus on the renewable energy generation, while it is not the only problem that China needs to solve before the 2030 carbon neutrality goals. As well, they need to ensure that the increment in demand is greater than the supply.

Reference

Acemoglu, D. (2009). *Introduction to modern economic growth*. Princeton University Press. https://doi.org/10.1515/9781400835775

Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation and work. *NBER Working Paper No. 24196*. National Bureau of Economic Research. https://doi.org/10.3386/w24196

Aghion, P., & Howitt, P. (1998). *Endogenous growth theory*. MIT Press. https://doi.org/10.7551/mitpress/6385.001.0001

Ahmed, A., Ge, T., Peng, J., Yan, W., Tee, B. T., & You, S. (2022). Assessment of the renewable energy generation towards net-zero energy buildings: A review. *Energy and Buildings, 256*, 111755. https://doi.org/10.1016/j.enbuild.2021.111755

Alharbi, S., Al Mamun, M., & Boubaker, S. (2023). Green finance and renewable energy: Worldwide evidence. *Energy Economics, 118.* 106499. http://dx.doi.org/10.1016/j.eneco.2022.106499

Aquilas, N.A., & Atemnkeng, J.T. (2022). Climate-related development finance and renewable energy consumption in greenhouse gas emissions reduction in the Congo basin. *Energy Strategy Reviews*, *44*, 100971. https://doi.org/10.1016/j.esr.2022.100971

Arfaoui, N., Naeem, M.A., Maherzi, T., & Kayani, U.N. (2024). Can green investment funds hedge climate risk? *Finance Research Letters, 60,* 104961. https://doi.org/10.1016/j. frl.2023.104961

Arrow, K. J., Chenery, H. B., Minhas, B. S., & Solow, R. M. (1961). Capital-labor substitution and economic efficiency. *The Review of Economics and Statistics, 43*(3), 225-250. https://doi.org/10.2307/1927286

Bai, J.C., Chen, Z.L., Yan, X., & Zhang, Y.Y. (2022). Research on the impact of green finance on carbon emissions: evidence from China. Economic *Research-Ekonomska Istrazivanja, 35* (1), 6965–6984. https://doi.org/10.1080/1331677X.2022.2054455

Barro, R. J. (1991). Economic growth in a cross-section of countries. *The Quarterly Journal of Economics, 106*(2), 407-443. https://doi.org/10.2307/2937943

Barro, R. J., & Sala-i-Martin, X. (2004). *Economic growth* (2nd ed.). MIT Press. https://doi.org/10.7551/mitpress/6699.001.0001

Bennagi, A., AlHousrya, O., Cotfas, D. T., & Cotfas, P. A. (2024). Comprehensive study of the artificial intelligence applied in renewable energy. *Energy Strategy Reviews. 54,* 101446 https://doi.org/10.1016/j.esr.2024.101446

Berndt, E. R., & Christensen, L. R. (1973). The translog function and the substitution of equipment, structures, and labor in U.S. manufacturing 1929–68. *Journal of Econometrics, 1*(1), 81-114. https://doi.org/10.1016/0304-4076(73)90007-9

Berrou, R., Dessertine, P., & Migliorelli, M. (2019). An Overview of Green Finance. The rise of Green Finance in Europe. *Palgrave Macmillan*, Cham. https://doi.org/10.1007/978-3-030-22510-0_1

Bidwell, D., & Sovacool, B.K. (2023). Uneasy tensions in energy justice and systems transformation. *nature energy, 8,* 317-320. https://doi.org/10.1038/s41560-023-01217-8

Bilal, M. J., & Shaheen W. A. (2023). Towards sustainable development: Investigating the effect of green financial indicators on renewable energy via the mediating variable. *Renewable Energy, 221*, 119819. https://doi.org/10.1016/j.renene.2023.119819

Bojek, P. (2025). *Renewables*. International Energy Agency. https://www.iea.org/energy-system/renewables#

Breusch, T., & Pagan, A. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *Review of Economic Studies, 47*(1), 239-253. https://doi.org/10.2307/2297111

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company. https://wwnorton.com/books/the-second-machine-age/

Chan, B. (2025). *How China is helping power the world's green transition*. World Economic Forum. https://www.weforum.org/stories/2025/01/why-china-matters-to-the-worlds-green-transition/

Chen, G (2024). *Energy-guzzling AI industry threatens China's green transition*. Think China. https://www.thinkchina.sg/technology/energy-guzzling-ai-industry-threatens-chinas-green-transition

Chen, J., Meng, W., Chen Y., & Zhou, W. (2024). To be an eco- and tech-friendly society: Impact research of green finance on AI innovation. *Journal of Cleaner Production, 466*, 142900. https://doi.org/10.1016/j.techsoc.2020.101257

Christensen, L. R., Jorgenson, D. W., & Lau, L. J. (1973). Transcendental logarithmic production frontiers. *The Review of Economics and Statistics, 55*(1), 28-45. https://doi.org/10.2307/1927992

Clifford Chance. (2024). *China issues guidelines on corporate sustainability reporting*. Retrieved from https://shorturl.at/oCOk2

Climate Change Law. (2021). *Action plan for carbon dioxide peaking before 2030 ('1+N').* https://climate-laws.org/document/action-plan-for-carbon-dioxide-peaking-before-2030-1-n_ee71

Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. *Technology in Society, 62*, 101257. https://doi.org/10.1016/j.techsoc.2020.101257

de La Grandville, O. (1997). Curvature and the elasticity of substitution: Straightening it out. *Journal of Economic Dynamics and Control*, *21*(2-3), 357-379. https://doi.org/10.1016/0165-1889(95)00900-6

Drechsler, W., Kattel, R., & Reinert, E. S. (2009). Techno-Economic Paradigms: Essays in Honour of Carlota Perez. *Anthem Press*. http://www.jstor.org/stable/j.ctt1gxpccq

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrics, 50(4),* 987-1007. https://doi.org/10.2307/1912773

Felipe, J. (2014). *Development and modernization: A quantitative history of Cobb-Douglas production functions*. Edward Elgar Publishing. https://doi.org/10.4337/9781784715540

Felipe, J., & Fisher, F. M. (2003). Aggregation in production functions: What applied economists should know. *Metroeconomica, 54*(2-3), 208-262. https://doi.org/10.1111/1467-999X.00162

Felipe, J., & McCombie, J. S. L. (2014). *The aggregate production function and the measurement of technical change: 'Not even wrong'*. Edward Elgar Publishing. https://doi.org/10.4337/9781784715519

Freeman, C. (1999). The Greening of Technology and Models of Innovation. *Technological Forecasting and Social Change*, *53* (1996), 27-39. https://doi.org/10.1016/0040- 1625(96)00060-1

Gayen, D., Chatterjee, R., & Roy, S. (2024). A review on environmental impacts of renewable energy for sustainable development. *International Journal of Environmental Science and Technology. 21*, 5285–5310. https://doi.org/10.1007/s13762-023-05380-z

Giacomo, D., Vincent, R. V., Daniel, V., & Marco, V. (2024). AI as a new emerging technological paradigm: evidence from global patenting. *GLO Discussion Paper No. 1467,* Global Labor Organization (GLO). https://hdl.handle.net/10419/300593

Green Finance & Development Centre. (2023). Green finance in China (3): Trends and recommendations for future development. https://greenfdc.org/green-finance-in-china-3-trends-and-recommendations-for-future-development/

Green Finance & Development Centre. (2024). New report: China green finance status and trends 2023-2024. https://greenfdc.org/china-green-finance-status-and-trends-2023-2024/

Greenfield, C. (2024). *Coal.* International Energy Agency. https://www.iea.org/energy-system/fossil-fuels/coal

Griffin, J. M., Montgomery, D., & Rister, M. (1987). Selection biases, technology effects, and the possibility of a CES production function bias. *Journal of Econometrics, 33*(1), 173-195. https://doi.org/10.1016/0304-4076(86)90036-1

Gu, G., Zhang, W., & Cheng, C., (2022). Mitigation effects of global low carbon technology financing and its technological and economic impacts in the context of climate cooperation. *Journal of Clean Production, 381*, 135182. https://doi.org/10.1016/j.jclepro.2022.135182

Hamdan, A., Ibekwe, K. I., Ilojianya, V. I., Sonko, S., & Etukudoh, E. A. (2024). AI in renewable energy: A review of predictive maintenance and energy optimization. *International Journal of Science and Research Archive 11*(01)*,* 718–729. https://doi.org/10.30574/ijsra.2024.11.1.0112

Hausfather, Z. & Friedlingstein, P. (2022). *Analysis: Global CO2 emissions from fossil fuels hits record high in 2022.* World Economic Forum. https://www.weforum.org/stories/2022/11/global-co2-emissions-fossil-fuels-hit-record-2022/

Hilton, I. (2024). *How China Became the World's Leader on Renewable Energy.* Yale Environment 360. https://e360.yale.edu/features/china-renewable-energy

Hulten, C. R. (2001). Total factor productivity: A short biography. In C. R. Hulten, E. R. Dean, & M. J. Harper (Eds.), *New developments in productivity analysis,* pp. 1-47. University of Chicago Press. https://doi.org/10.7208/chicago/9780226360645.003.0001

Humphrey, T. M. (1997). Algebraic production functions and their uses before Cobb-Douglas. *Economic Quarterly, 83*(1), 51-83. https://www.richmondfed.org/-/media/RichmondFedOrg/publications/research/economic_quarterly/1997/winter/pdf/humphrey.pdf

Ian, T. (2025, January 15). Annual global emissions of carbon dioxide 1940-2023 [Graph]. Statista. https://www.statista.com/statistics/276629/global-co2-emissions/

International Association for Energy Economics. (2024). The impact of AI of the energy sector in China. IAEE Energy Forum, 2024 (2nd Quarter), 5-7. https://www.iaee.org/en/publications/newsletterdl.aspx?id=1085#:~:text=AI%20is%20making%20big%20waves,opportunities%20and%20challenges%20it%20brings.

International Carbon Action Partnership (ICAP). (2024). *China national emissions trading system (ETS)*. Retrieved from https://icapcarbonaction.com/en/ets/china-national-ets

International Energy Agency [IEA]. (2023). Coal 2023. https://www.iea.org/reports/coal-2023#overview

International Energy Agency [IEA]. (2024a). *Share of renewable electricity generation by technology, 2000-2008*. https://www.iea.org/data-and-statistics/charts/share-of-renewable-electricity-generation-by-technology-2000-2028

International Energy Agency [IEA]. (2024b). *Massive expansion of renewable power opens door to achieving global tripling goal set as COP28* https://www.iea.org/news/massive-expansion-of-renewable-power-opens-door-to-achieving-global-tripling-goal-set-at-cop28

International Energy Agency [IEA]. (2024c). *Renewables 2023*, Paris. https://www.iea.org/reports/renewables-2023

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters, 6*(3), 255–259. https://doi.org/10.1016/0165-1765(80)90024-5

Jeniffer, L. (2025). China's Renewable Energy Boom: A Record-Breaking Shift or Still Chained to Coal? Carbon Credits.com https://carboncredits.com/chinas-renewable-energy-boom-a-record-breaking-shift-or-still-chained-to-coal/#:~:text=In%202020%2C%20China%20set%20a,6%20years%20ahead%20of%20schedule.

Jin, Y., Gao, X. & Wang, M., (2021). The financing efficiency of listed energy conservation and environmental protection firms: Evidence and implications for green finance in China. *Energy Policy, 153*, 112254. https://doi.org/10.1016/j.enpol.2021

Khan, Z., Ali, S., Dong, K., & Li, R.Y.M. (2021). How does fiscal decentralization affect CO2 emissions? The roles of institutions and human capital. *Energy Economics, 94,* 105060. https://ideas.repec.org/r/eee/eneeco/v94y2021ics014098832030400x.html

Lee, C., Li, X., Yu, H. & Zhao, J. (2022). The contribution of climate finance toward environmental sustainability: New global evidence. *Energy Economics, 82,* 103439. https://doi.org/10.1016/j.resourpol.2023.103439

Lee, C.C., Qin, S., & Li, Y. (2022b). Does industrial robot application promote green technology innovation in the manufacturing industry? *Technological Forecasting Social Change. 183*, 121893. https://doi.org/10.1016/j.techfore.2022.121893

Lee, C.C., Wang, F., & Chang, Y.F., (2023). Does green finance promote renewable energy? Evidence from China, *Resources Policy, 82*, 103439. https://doi.org/10.1016/j.resourpol.2023.103439

Li, J., Dong, K., Taghizadeh- Hesary, F., & Wang, K. (2022). 3G in China: How green economic growth and green finance promote green energy. *Renewable Energy. 200*, 1327-1337. https://doi.org/10.1016/j.renene.2022.10.052

Li, J., Ma, S., Qu, Y., & Wang, J. (2023). The impact of artificial intelligence on firms' energy and resource efficiency: empirical evidence from China. *Resources Policy, 82,* 103507. https://doi.org/10.1016/j.resourpol.2023.103507

Li, Y., Zhang, Y., Pan, A., Han, M., & Veglianti, E. (2022). Carbon emission reduction effects of industrial robot applications: Heterogeneity characteristics and influencing mechanisms. *Technology in Society, 70*, 102034. https://doi.org/10.1016/j.techsoc.2022.102034

Lin, C., Xiao, S., Yin, Z. (2022). How do industrial robots applications affect the quality upgrade of Chinese export trade? *Telecommunication Policy, 46* (10), 102425. https://doi.org/10.1016/j.telpol.2022.102425

Liu H., Evans, S., Zhang, Z., Song, W., & You, X. (2023). The Carbon Brief Profile: China. Carbon Brief. https://interactive.carbonbrief.org/the-carbon-brief-profile-china/index.html

Liu, Y. (2024, August 20). Further application of smart solution in green energy sector seen as key. China Daily. https://www.chinadaily.com.cn/a/202408/20/WS66c3f09fa31060630b923eec.html

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), 3-42. https://doi.org/10.1016/0304-3932(88)90168-7

Lyons-Chuna, J. (2025). *AI Energy Consumption: Is It a Problem.* Built in https://builtin.com/artificial-intelligence/ai-energy-consumption

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics, 107*(2), 407-437. https://doi.org/10.2307/2118477

Manuel, H. N. N., Kehinde, H. M., Agupugo, C. P., & Manuel, A. C. N. (2024). The impact of AI on boosting renewable energy utilization and visual power plant efficiency in contemporary construction. *World Journal of Advanced Research and Reviews 2024, 23*(02), 1333–1348. https://doi.org/10.30574/wjarr.2024.23.2.2450

Mathews, J. A. (2012). The renewable energies technology surge: A new techno-economic paradigm in the making? *Futures, 46 (2013),* 10-22. https://doi.org/10.1016/j.futures.2012.12.001

Matschoss, P., Bayer, B., Thomas, H., & Marian, A. (2019). The German incentive regulation and its practical impact on the grid integration of renewable energy systems. *Renewable Energy, 134,* 727-738. https://doi.org/10.1016/j.renene.2018.10.103

Naeem, M.A., Appiah, M., Taden, J., Amoasi, R., & Gyamfi, B.A. (2023). Transitioning to clean energy: assessing the impact of renewable energy, bio-capacity and access to clean fuel on carbon emissions in OECD economies. *Energy Economics. 127,* 107091, https://doi.org/10.1016/j.eneco.2023.107091

Narayan, P. K. (2005). The Saving and Investment Nexus for China: Evidence from Cointegration Tests. *Applied Econometrics, 37* (17), 1979-1990. https://doi.org/10.1080/00036840500278103

Nepal, R., Zhao, X., Dong, K., Wang, J., & Sharif, A. (2025). Can artificial intelligence technology innovation boost energy resilience? The role of green finance. *Energy Economics, 142,* 108159. https://doi.org/10.1016/j.eneco.2024.108159

Nguyen, T.T.H., Naeem, M.A., Balli, F., Balli, H.O., Vo, X.V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters, 40*, 101739. https://doi.org/10.1016/j.frl.2020.101739

Perez, C. (2009). Technological revolutions and techno-economic paradigms. *Cambridge Journal of Economics, 34* (2010), 185-202. https://doi.org/10.1093/cje/bep051

Pesaran, M.H, Shin Y., & Smith. R.J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics, 16* (3), 289-326. https://www.jstor.org/stable/2678547?seq=2

Phillips, P. C. B., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. Biometrika, 75(2), 335–346. https://doi.org/10.2307/2336182

Proctor, D. (2025). *Coal Continues to Lead China's Record Levels of Power Generation.* POWER. https://www.powermag.com/coal-continues-to-lead-chinas-record-levels-of-power-generation/

Qi, H., Huang, X., & Sheeraz, M. (2023). Green financing for renewable energy development: Driving the attainment of zero emission targets. *Renewable Energy, 213*, 30–37. https://doi.org/10.1016/j.renene.2023.05.111

Qiang, W., Li, Y., & Li, R. (2025). Integrating artificial intelligence in energy transition: A comprehensive review. *Energy Strategy Reviews.* 57, 101600. https://doi.org/10.1016/j.esr.2024.101600

Ramzani, S. R., Konhaeusner, P., Olaniregun, O. A., Abu-Alkheil, A., & Alsharari, N. (2024). Integrating AI-Driven Green Finance Strategies for Sustainable Development: A Comparative Analysis of Renewable Energy Investments in Germany and Denmark. *European Journal of Business and Management Research*, *9*(2), 43–55. https://doi.org/10.24018/ejbmr.2024.9.2.2277

Rasheed, M. Q., Zhao, Y., Haseeb, A., & Ahmed, Z. (2024). Asymmetric relationship between competitive industrial performance, renewable energy, industrialization, and carbon footprint: Does artificial intelligence matter for environmental sustainability? *Applied Energy, 367*, 123346. https://doi.org/10.1016/j.apenergy.2024.123346

Rasoulinezhad, E., & Taghizadeh-Hesary, F. (2022). Role of green finance in improving energy efficiency and renewable energy development. *Energy Efficiency*, *15*, 14. https://doi.org/10.1007/s12053-022-10021-4

Rhodes, A. (2020). *Digitalisation of Energy.* Imperial Collage London, 1-48. https://spiral.imperial.ac.uk/bitstream/10044/1/78885/2/4709_EFL_Digitalisation_briefing_paper_WEB2.pdf

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy, 94*(5), 1002-1037. https://doi.org/10.1086/261420

Sadiq, M., Paramaiah, C., Joseph, R., Dong, Z., Nawaz, M. A., & Shukurullaevich, N. K. (2023). Mediating role of environmental regulations and government interventions in the pre-post COVID eras. *Resources Policy 88,* 104494. https://doi.org/10.1016/j.resourpol.2023.104494

Sangiorgi, I., & Schopohl, L. (2021). Why do institutional investors buy green bonds: evidence from a survey of European asset managers. *International Review of Financial Analysis*, 75, 101738. https://doi.org/10.1016/j.irfa.2021.101738

Shajar, S. N., Kashif, M., George, J., & Nasir, S. (2024). The Future of Green Finance: Artificial Intelligence-Enabled Solutions for a More Sustainable World. *Harnessing Blockchain-Digital Twin Fusion for Sustainable Investments.* 316-328. https://doi.org/10.4018/979-8-3693-1878-2.ch013

Shin, W., Han, J., & Rhee, W. (2021). AI-assistance for predictive maintenance of renewable energy systems. *Energy, 221*, 119775. https://doi.org/10.1016/j.energy.2021.119775

Sinha, A., Ghosh, V., Hussain, N., Nguyen, D. K., & Das, N. (2023). Green financing of renewable energy generation: Capturing the role of exogenous moderation for ensuring sustainable development. *Energy Economics, 126*, 107021. https://doi.org/10.1016/j.eneco.2023.107021

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics, 70*(1), 65-94. https://doi.org/10.2307/1884513

Taghizadeh-Hesary, F., Dong, K., Zhao, C., & Phoumin, H. (2023). Can financial and economic means accelerate renewable energy growth in the climate change era? The case of China. *Economic Analysis Policy. 78*, 730–743. https://doi.org/10.1016/j.eap.2023.04.013

Tang, X. & Zhou, X. (2023). Impact of green finance on renewable energy development: A spatiotemporal consistency perspective. *Renewable Energy, 204.* 320-337. https://doi.org/10.1016/j.renene.2023.01.012

Tawney, L., & Weischer, L., (2021). Innovation and Technology Transfer: Supporting Low Carbon Development with Climate Finance. *World Resources Institute Working Paper*. http://pdf.wri.org/working_papers/innovation_&_technology_transfer.pdf

The people's Bank of China. (2016). Guidelines for Establishing the Green Financial System. http://www.pbc.gov.cn/english/130721/3133045/index.html

Tian, L., Li, X., Lee, C., & Spulbar, C. (2024). Investigating the asymmetric impact of artificial intelligences on renewable energy under climate policy uncertainty. *Energy Economics, 137*, 107809. https://doi.org/10.1016/j.eneco.2024.107809

Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T.-C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment*, *35 (7),* 3833-3879. https://doi.org/10.1177/0958305X241256293

Wang, B. & Zhao, W., 2022. Interplay of renewable energy investment efficiency, shareholder control and green financial development in China. *Renewable Energy ,199*, 192–203. https://doi.org/10.1016/j.renene.2022.08.122

Wang, B., Wang, J., Dong, K., & Nepal, R. (2024). How does artificial intelligence affect high-quality energy development? Achieving a clean energy transition society. *Energy Policy, 186,* 114010. https://doi.org/10.1016/j.enpol.2024.114010

Wang, J., Wang, K., Dong, K., & Zhang, S. (2023a). Assessing the role of financial development in natural resource utilization efficiency: Does artificial intelligence technology matter? *Resources Policy, 85*, 103877. https://doi.org/10.1016/j.resourpol.2023.103877

Wang, J., Wang, W., Liu, Y. & Wu, H., 2023b. Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China. *Technology in Society. 72*, 102208. https://doi.org/10.1016/j.techsoc.2023.102208

Wang, Q., Li, Y., & Li, R., (2025) Integrating artificial intelligence in energy transition: A comprehensive review. *Energy Strategy Reviews, 57*, 101600. https://doi.org/10.1016/j.esr.2024.101600

World Meteorological Organization. (2025, January 10). *WMO confirms 2024 as warmest year on record at about 1.55°C above pre-industrial level*. https://wmo.int/news/media-centre/wmo-confirms-2024-warmest-year-record-about-155degc-above-pre-industrial-level#

Xiong, Y., & Dai, L. (2023). Does green finance investment impact on sustainable development: Role of technological innovation and renewable energy. *Renewable Energy, 214,* 342-349. https://doi.org/10.1016/j.renene.2023.06.002

Xu, Y., Ahokangas, P., Louis, J.N. & Pongr´acz, E. (2019). Electricity market empowered by artificial intelligence: A platform approach. *Energies, 12* (21), 4128. https://doi.org/10.3390/en12214128

Xue, Y. (2024, July 11). Chinese tech giants trail on renewable energy use, and AI will put them further behind. *South China Morning Post.* https://www.scmp.com/business/china-business/article/3269954/chinese-tech-giants-trail-renewable-energy-use-and-ai-will-put-them-further-behind?module=top_story&pgtype=section

Yang, M., & Zhang, S. (2024). *China*. EMBER. https://ember-energy.org/countries-and-regions/china/

Yang, W., & Wang, D. (2023). Can industrial robot applications help cross the middleincome trap? —empirical evidence based on crossed-country panel data. *Technology Forecasting and Social Change. 192,* 122583. https://doi.org/10.1016/j.techfore.2023.122583

Yu, L., Wang, Y., Wei, X., & Zeng, C. (2023). Towards low-carbon development: the role of industrial robots in decarbonization in Chinese cities. *Journal of Environmental Management, 330*, 117216. https://doi.org/10.1016/j.jenvman.2023.117216

Zeng, J., Wang, Z., & Yu, X. (2021). The impact of AI adoption on industrial productivity: A Cobb-Douglas perspective. *Journal of Economic Development, 46*(4), 127-153. https://doi.org/10.35866/caujed.2021.46.4.006

Zhang, L., Ling, J., & Lin, M. (2022). Artificial intelligence in renewable energy: A comprehensive bibliometric analysis. *Energy Reports 8*, 14072-14088. https://doi.org/10.1016/j.egyr.2022.10.347

Zhang, P., Li, Z., Ghardallou, W., Xin, Y., & Cao, J. (2023). Nexus of institutional quality and technological innovation on renewable energy development: Moderation role of green finance. *Renewable Energy, 214*, 233-241. https://doi.org/10.1016/j.renene.2023.05.089

Zhang, X., Khan, K., Shao, X., Oprean-Stan, C., & Zhang, Q. (2024). The rising role of artificial intelligence in renewable energy development in China. *Energy Economics, 132*, 107489. https://doi.org/10.1016/j.eneco.2024.107489

Zhang, Y., & Da, L. (2020). Green growth and AI-driven productivity in the new industrial revolution: Extending the Cobb-Douglas model. *Sustainability, 12*(24), 10347. https://doi.org/10.3390/su122410347

Zhao, C., Dong, K., Wang, K., & Nepal, R. (2024). How does artificial intelligence promote renewable energy development? The role of climate finance. *Energy Economics, 133*(C), 107493. https://doi.org/10.1016/j.eneco.2024.107493

Zhao, C., Wang, J., Dong, K., & Wang, K. (2023c). How does renewable energy encourage carbon unlocking? A global case for decarbonization. *Resources Policy. 83*, 103622. https://doi.org/10.1016/j.resourpol.2023.103622

Zhao, C., Wang, K., Dong, X. & Dong, K. (2022a). Is smart transportation associated with reduced carbon emissions? The case of China. *Energy Economics.* 105, 105715. https://doi.org/10.1016/j.eneco.2021.105715

Zhao, E., Sun, S., & Wang, S. (2022). New developments in wind energy forecasting with artificial intelligence and big data: A scientometric insight. *Data Science and Management. 5 (2),* 84–95. https://doi.org/10.1016/j.dsm.2022.05.002.

Zhao, J., Jiang, Q., Dong, X., Dong, K., & Jiang, H. (2022d). How does industrial structure adjustment reduce CO2 emissions? Spatial and mediation effects analysis for China. *Energy Economics*. 105 (105704), 1-17. https://doi.org/10.1016/j.eneco.2021.105704

Zhou, G.Y., Zhu, J. Y., & Luo, S. M. (2022). The impact of fintech innovation on green growth in China: mediating effect of green finance. *Ecological Economics, 193*, 107308. https://doi.org/10.1016/j.ecolecon.2021.107308