

Integrating AI-Driven Green Finance Strategies for Sustainable Development: A Comparative Analysis of Renewable Energy Investments in Germany and Denmark

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ABSTRACT

This research explores the convergence of synthetic intelligence (SI) and inexperienced finance techniques in influencing the development of renewable power sectors, with a specific focus on Denmark and Germany for the critical periods of 2019 and 2020. ANOVA, paired sample t-tests, and regression analysis were used as part of a strict method to look into how the production of renewable energy has changed and how AI-driven financial techniques have affected it. The results spotlight the effectiveness of AI-driven green finance solutions in bringing approximately enormous ameliorations, establishing Denmark as a probable exemplar for sustainable progress. In evaluation, Germany's consistent power infrastructure, blended with a fantastic correlation exposed in regression evaluation, highlights the durability of its environmentally pleasant economic methods. This study presents a well-timed and informative guide for developing effective, inexperienced finance rules that guide a greener and more sustainable future as international locations all around the world address environmental-demanding situations.

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1. INTRODUCTION

Given the urgency of the climate alternate disaster, it's crucial to acquire sustainable growth by incorporating AI into the inexperienced economic system. A game-changer in economics, the mixing of AI into an inexperienced economic system places environmental protection at the forefront. This advent seeks to provide context, emphasize motivation, and emphasize the significance of AI-powered green finance, with a specific focus on doing a comparative evaluation of investments in renewable power in Germany and Denmark. With increasing international focus on an ecologically sustainable future, the mixing of synthetic intelligence (SI) with inexperienced finance plays a crucial role in enabling virtual transformation and revolutionizing economic practices. In this introductory segment, we investigate on implications and highlighted how crucial AI-pushed methods are for reaching sustainable development goals in Germany and denmak. In the

elements that we observe, we are able to study positive research subjects and theories, delving into the complex dynamics of investments in renewable energy in exceptional countrywide settings (Kumar *et al.*, 2022a).

1.1. Background

Current economic growth is characterized by the pervasive influence of modernization and AI technology. The rise of electronic finance has been a game-changer for international trade and financial institutions and is radically altering the global distribution of resources. Environmental degradation and climate change now pose unprecedented challenges around the world (Kulkov *et al.*, 2023).

1.2. Motivation

As a key economic driver, the banking industry can contribute to reducing global warming and other environmental damage. Digital innovation is needed to



overcome these barriers, promote sustainable development, and find new ways to reduce greenhouse gas emissions. Achieving the Sustainable Development Goals requires a combination of the green economy, technology, and other resources. Since AI-driven, processes have the potential to dramatically change environmental perceptions and influence economic decision-making; these processes should be integrated into a green economy (Mehta et al., 2023).

1.3. Importance of AI-Powered Green Finance

Artificial intelligence plays a key role in the green economy to generate monetary and environmental rewards. Climate investing and sustainable finance are increasingly important, and AI is a great tool to help with decision-making, risk management, and investment in environmentally friendly projects around the world. The green economy that incorporates AI accelerates sustainable business by matching corporate profitability with social and environmental responsibility. When financial institutions use AI to improve data analytics, strengthen risk management, and optimize decision-making processes to support sustainability goals, there can be benefits for society and long-term environmental impact. The aim of the study is to explore AI-driven strategies in Germany and Denmark to make their green economy projects more efficient and effective with renewable energy. This includes exploring artificial intelligence (AI) applied to project financing, analyzing risk factors, and increasing the resources allocated for sustainable energy projects (Moşteanu, 2023).

1.4. The Role of Green Finance in Driving the Adoption of Renewable Energy

The discourse on green economy development emphasizes its role as an incentive for companies to engage in environmentally sustainable practices and distribute environmentally friendly products. The study will look at how Germany and Denmark use green finance to boost renewable energy infrastructure, including solar, wind, sustainable energy, and property. As emphasized in the discussion, the importance of harmonized national policies is closely linked to comparative research. The cooperative analysis of German and Danish national policies, particularly in the field of renewable energy, provides valuable insights into the effectiveness of their sustainable economic policies. The impact of the green economy on agriculture, particularly organic farming, shows parallels with sustainable approaches to renewable energy (Lee et al., 2023).

1.5. Limitations

The chosen time period (2019–2020) provides modern knowledge but fails to capture long-term trends or changes beyond 2020 due to global events, including the COVID-19 pandemic. The studies' focus on quantitative analysis may lead to the overlooking of qualitative forces and stakeholder perspectives, which may be important for the integration of AI in an inexperienced financial sector. In summary, it is crucial to identify them correctly to support the reliability and validity of the study findings and to address the limitations of this study, which are the most

important issues for AI in Germany and Denmark (Zakari et al., 2022).

1.6. Hypotheses

The study theme is linked to the following research questions or hypotheses:

- Is there any positive impact of increase in energy production in 2020 as compared to 2019 because of the use of AI-driven technologies?
- Is there a positive impact of AI-driven techniques in energy production in 2020 or not as compared to 2019?

This study aims to address the aforementioned challenges in sustainable development, the green economy, and artificial intelligence (AI) and to establish the expansion of renewable energy in Germany, with special emphasis on Denmark.

The paper is structured into six sections. Section 1 presents and underscores green finance strategies aimed at fostering the sustainable development of renewable resources. Section 2 presents a comprehensive literature review, providing a synopsis of the current understanding of the topic. Section 3 examines the utilization of artificial intelligence in green finance strategies, investigating the convergence of AI and sustainable finance. Section 4 provides a detailed explanation of the technique used in the study. Section 5 highlights and examines the results that were achieved. Section 6 provides a concluding section that presents a concise summary of the main findings and the potential implications they have for the study.

2. LITERATURE REVIEW

According to (Yigitcanlar et al., 2021) Smart cities and artificial intelligence (AI) have been hot topics in urban policy circles, but putting AI to work to boost municipal efficiencies has been difficult, mostly because people have been too reductionist and have failed to see the whole picture. The need for an environmentally friendly AI strategy arose within the smart city framework as a means to achieve efficiency, sustainability, and equality. To facilitate the transition to smart cities, this perspective paper outlines the main problems with current AI theory and proposes a unified strategy green AI (Gozgor et al., 2020).

Findings from studies examining the growth of green finance and clean energy generally have important consequences for attaining systemic transformation in the energy industry and long-term financial growth Zhao et al. (2023), constructed an interaction degree of collaboration framework for the system to investigate potential synergies between green financing and renewable energy. It's not well known how the variables that affect coupling coordination are connected to each other, but a fuzzy set qualitative comparative analysis (fsQCA) method was created to look at various alignment methods. Chinese empirical data shows that the pair's coordination degree increased from 0.3341 in 2011 to 0.4718 in 2020; however, it remained nearly imbalanced. As degrees of regional coordination developed unevenly, a tendency toward high-value clustering emerged. The study found that one way

to encourage the coordinated expansion of green financing and clean energy was for provinces to tailor their policies to the specific characteristics and configurations of their own regions. The fsQCA method offered a new way of looking at existing paths to better understand the cooperative expansion of green financial services and clean energy in China's provinces. The results shed light on the necessity for provincially specific regulations while enhancing our understanding of the interconnected growth of green finance and clean energy.

Banking institutions are starting to see the need to change their business models to be more environmentally responsible in order to meet the growing global need for more corporate involvement in sustainable development (Cesário et al., 2022). The recognition of this fact has resulted in the development of the notion of green finance. Despite extensive progress over many years, there is still no globally agreed-upon definition for the phrase "green finance" (Khan et al., 2022b). Green finance is characterized by its utilization of financial innovation to advance the protection of the environment, distinguishing it from normal finance. Green finance is asserted to serve as a financial instrument that enables firms to tackle environmental concerns and advance environmental preservation across society. China has become the leading country in the world in creating a thorough system for green financing. Green finance is officially defined by the country as a business venture that fosters environmental betterment, global warming prevention, and resource efficiency. Additionally, it includes the offering of monetary assistance for environmentally friendly projects. Essentially, the definitions described above emphasize that green finance is a financing tool that supports efforts to protect the environment and promote sustainable development, specifically in reducing carbon emissions.

The importance of clean energy in fostering environmentally friendly growth and attracting investment in sustainable finance cannot be overstated (Wang et al., 2021). The majority of the current literature investigates how green funding affects renewable energy. This evaluation takes into account a number of factors, including consumption (Liu & Tang, 2022), availability (Wang et al., 2022), capital (Zhang, 2022), and cost correlations (Hammoudeh et al., 2020; Tiwari et al., 2022). The majority of studies that have looked at this issue have shown that green banking has a lot of positive effects on several aspects of encouraging clean energy. Other academics have looked more deeply into clean energy's significance within the context of green finance. Nawaz et al. (2021) and (Bei & Wang, 2023), respectively, used wavelet coherence techniques to illustrate a one-way causal connection between energy investment and green financing over a specific timeframe.

In thirty OECD countries from 1975 to 2015, Khan et al. (2022a) study examined the phenomenon of economic globalization. International Relations, Development (OECD) members, and other developed and developing nations are all subject to these criteria (Iram et al., 2020; Mohsin et al., 2019, 2018). According to Heine et al. (2019), to transition to a low-carbon economy and successfully reduce the effects of climate change, carbon pricing and green bonds must be adopted and

put into action. From 2008 to 2017, according to official reports, Tolliver et al. (2020) discovered that national finances (NDCs) significantly affected the distribution of green bond profits to clean energy. Their article claims that renewable energy assets and projects receive a larger portion of bond proceeds—exactly 99%—when stringent nationally established contributions (NDCs) are put in place.

From 18% to 29%, the climate funding coefficient of MDBs has climbed over 61% since 2013. (Tanner & Horn-Phathanothai, 2019) Funds of \$30,165 million were disbursed in 2018 to combat climate change by multilateral development banks (MDBs). Investment loans provided the majority of this sum, or \$21,439 million, or 71%. The program-based financing component also received 7% of the \$2,195,000,000 total. The sustainable economy in the Americas was the focus of Yuan and Gallagher's 2018 research. They emphasized the significance of addressing the \$110 billion annual deficit that multilateral development banks (MDBs) are currently uncovering. Multilateral development banks (MDBs) have allocated \$7 billion to the green economy, they said, with an annual budget of \$4.4 billion allocated specifically for climate change mitigation in these areas. Furthermore, their study suggests that countries with higher human rights records and post-socialist ideologies may attract more financial support for environmental policy from MDBs (Yuan & Gallagher, 2018). According to a recent study by Sinha et al. (2020), the failure of N-11 countries to sustain environmental sustainability posed challenges in their efforts to achieve the Sustainable Development Goals (SDGs). Moreover, the N-11 countries have put economic growth at the expense of the environment.

The report, both on green finance and clean energy, fills the gap in current research and reveals a comprehensive analysis of the interactions between states. The proposed systematic approach for the audit evaluation workshop is consistent with the objective of the report, which is to identify investments in renewable energy in a variety of national contexts. A systematic approach is important when comparing renewable energy investments in Germany and Denmark. It enables research on the impact of advances in clean energy on AI-driven green distribution strategies. This approach improves the overall evaluation by providing a quantitative framework for assessing the effectiveness of AI-driven strategies in achieving sustainable development goals.

3. ARTIFICIAL INTELLIGENCE-POWERED GREEN FINANCE STRATEGIES

Artificial intelligence (AI) is increasingly having an impact on the sustainable economy, with ultra-green investment strategies being developed and set for a movement that can drive change. This section explores the theoretical and conceptual foundations that contribute to the fusion of AI and the green economy, choosing to focus on its application in renewable electricity investments (Kumar et al., 2022b).

3.1. Theoretical Framework

One of the key features is the ability of AI to efficiently analyze large chunks of information and extract insights to be treasured. Machine-acquired knowledge of algorithms, which may be a subset of artificial intelligence (AI), facilitates the identification of complex patterns and trends in environmental and economic data. The theoretical foundation is derived from the ability of AI to develop predictive models. AI systems can anticipate the potential risks and rewards of renewable energy investments using raw, real-time data. The ability to predict future results improves the strategic planning and risk management of inexperienced economies, creating potentially flexible investment models that yield good results (Liu et al., 2022).

3.2. Conceptual Basis

Important tips for integrating AI into inexperienced financial systems: the goals of AI are to improve resource allocation, reduce risk, and encourage innovation (Ahmad et al., 2021).

- *Data-Driven Decision Making:* Artificial intelligence permits practitioners within the area of green finance to make decisions primarily based on record evaluation. AI permits a detailed comprehension of the renewable power region with the aid of analysing numerous records regarding climate patterns, the manufacturing of electricity, and marketplace tendencies. Consequently, this affects strategic investment choices (Bachmann et al., 2022).
- *Evaluation and Minimization of Risks:* AI algorithms reveal brilliant performance in danger evaluation through the evaluation of past information and the identification of capability hazards. Within the area of green-strength investments, this involves adopting a proactive approach to address uncertainties, guarantee the lengthy-term sustainability of projects, and defend monetary pastimes (Danish & Senjyu, 2023).
- *Algorithmic Trading for Green Investments:* The combination of artificial intelligence (AI) and green finance is evident in algorithmic trading, with AI-powered algorithms trading independently according to predefined criteria. In the case of renewable energy, this enables better real-time monitoring of portfolios, which instantly adapts to market developments and regulatory changes (Ning, 2021).

3.3. AI Applications in Renewable Energy Investments

The realistic uses of AI in the realm of renewable energy tasks are many and substantial. The following objects are covered:

- *Forecasting Analysis for Energy Generation:* AI design can determine the amount of electricity generated from renewable sources. It can help in planning and optimizing the integration of solar, wind, and other sustainable sources into the energy grid (Serban & Lytras, 2020).

- *Smart Grid Management:* AI plays a key role in the development of smart grids and improves the efficiency and reliability of renewable electricity distribution systems. These include proactive protection, demand forecasting, and grid optimization in real time.
- *Carbon Footprint Analysis:* Artificial intelligence AI is critical to researching and reducing the environmental impact of renewable energy operations. By analyzing facts throughout the project lifecycle, artificial intelligence identifies areas that may have been significantly improved (Gaur et al., 2023)

Specifically, the conceptual basis for incorporating AI into sustainable economic planning requires the use of state-of-the-art computing skills to overcome the complexity of renewable energy projects using AI, especially in the sustainable green economy, by improving decision-making and increasing business efficiency.

4. METHODOLOGY

The method requires two different classifications, for which the 2019 and 2020 periods were analyzed using a balanced data set. The analysis uses paired sample t tests, regression analyses, ANOVA, and descriptive statistics to test for differences in individual characteristics across locations and provides a comprehensive analysis. The study calls for a comprehensive review of green finance and sustainable development policies in the critical years of 2019 and 2020, ensuring the methodology, sample size, and timing of the analysis are consistent.

4.1. Data Sampling

This empirical study uses quantitative methods to analyze Denmark and Germany. All tracks are considered heterogeneous due to geographical and demographic differences. The paired sample t test emphasizes that the study uses track regression analysis.

This method can take into account intrinsic heterogeneity by considering the variety of the random term. Data obtained rigorously from various online sources from destatics and dnk government portals guarantees a comprehensive dataset, which is crucial for ensuring the credibility of the study. This analytical framework offers a rigorous analysis that illuminates the interaction between green finance strategies and sustainable development in the specific settings of Denmark and Germany. The study examines the incorporation of AI-powered green finance tactics to promote sustainable development, with a specific emphasis on conducting a comparative assessment of investments in renewable energy between Germany and Denmark. The study consists of two diverse cross-sections that cover the time span from 2019 to 2020. The data is analysed using a balanced set of data approaches to evaluate the influence of green money on environmental sustainability. Considering that Germany and Denmark are the dominant industries in the areas they represent, each country is compared to other regions separately (Rasouli & Yu, 2019).

Table I displays information regarding the proportion of renewable energy sources in Denmark's home electricity

TABLE I: ELECTRICITY GENERATED BY RENEWABLE SOURCES: PROPORTION OF DENMARK'S RESIDENTIAL POWER SUPPLY

Energy sources	2019		2020	
	Billion kWh	(%)	Billion kWh	(%)
Renewable energy	119.025	67.5	122.579	68.0
Solar	3.468	2.8	4.250	3.4
Wind	58.139	46.8	58.789	47.0
Hydro	61	0.0	61	0.0
Biomass	51.360	15.1	53.340	22.0
Straw	4.653	1.4	4.963	2.0
Wood	36.383	11.0	37.518	17.4
Biooil	0	0.0	0	0.0
Waste, renewable	10.324	2.8	10.860	2.7
Biogas	5.996	2.4	6.139	2.5

TABLE II: GROSS ELECTRIC PRODUCTION IN GERMANY FROM 2019 TO 2020

Energy sources	2019		2020	
	Billion kWh	%	Billion kWh	%
Gross electricity production, Total	602.3	100	568.1	100
Lignite	114	18.7	91.7	16
Hard coal	57.5	9.5	42.8	7.4
Nuclear energy	75.1	12.3	64.4	11.2
Natural gas	89.9	14.8	94.7	16.5
Mineral oil products	4.8	0.8	4.7	0.8
Renewable energy sources	241.6	39.7	251.1	43.8
Wind power	125.9	20.7	132.1	23
Water power ³	20.1	3.3	18.7	3.3
Biomass energy	44.3	7.3	45.1	7.8
Photovoltaic energy	45.2	7.4	49.5	8.6
Household waste ⁴	5.8	1	5.8	1
Geothermal	0.2	0	0.2	0
Other energy sources	25.4	4.2	24.8	4.3

supply. The table specifically highlights different components such as solar, wind, hydro, biomass, straw, wood, biooil, trash (renewable), and biogas. The statistics are expressed in billion kilowatt-hours (billion kWh), along with the corresponding percentage breakdown for each energy source in both 2019 and 2020. Through analysing the proportion of power generated from various sources of renewable power, we can evaluate the efficacy of green financial strategies in advancing a sustainable energy blend (Rose et al., 2022).

Table II, presenting the gross electric production in Germany from 2019 to 2020, offers a thorough depiction of the nation's energy panorama. The data is displayed in billion kilowatt-hours (billion kWh), along with the corresponding percentage breakdown for each energy source in both years. Various energy sources are taken into account in the analysis, which includes lignite, hard coal, nuclear power, natural gas, mineral oil products, renewable power, and targeted renewables like wind power, water power, biomass power, photovoltaic power, geothermal, and other atypical sources (Keles & Yilmaz, 2020).

4.2. Statistical Testing

The statistical analysis included advanced tests of rigorous data analysis, such as significance testing, paired sample t-tests, regression analyses, and ANOVA (Hahs-Vaughn & Lomax, 2020).

4.2.1. Descriptive Statistics

Descriptive statistics play an important role in our analysis of the integration of AI-driven green finance mechanisms for sustainable development in Germany and Denmark, helping us explore the robust renewable energy sources in which we live. Our analysis of the "Sustainable Energy to Electricity" table for Denmark focuses on calculating key variables such as mean, median, and standard deviation. By examining key trends, conversions, and distribution patterns, we can gain useful insights into the complexity of Denmark's renewable energy supply. At the same time, the illustrated table "Gross Electricity Generation in Germany from 2019 to 2020" forces a comparative descriptive statistical analysis. The aim of our study is to highlight trends in electricity sources through mean, median, and standard deviation calculations (Mishra et al., 2019).

4.2.2. Paired Sample T-Test

The use of the paired sample t-test is important in our analysis of AI-driven sustainable finance in Germany and Denmark, as it allows us to examine paired data points. This statistical method examines the magnitude of anomalies in each country, including investment in renewable energy. It plays a key role in analyzing statistical changes over time and provides valuable information on the impact

TABLE III: PAIRED SAMPLE T-TEST

Pair	Billion kWh-Billion kWh	Paired differences				t	df	Sig. (2-tailed)	
		Mean	Std. deviation	Std. error mean	95% confidence interval of the difference				
					Lower				Upper
Pair 1	Billion kWh-Billion kWh	-909.000	1106.275	349.835	-1700.381	-117.619	-2.598	9	0.029

of an AI-driven green economy on economic and environmental outcomes (Bhatti et al., 2019).

4.2.3. Regression Analysis

For our study of AI-driven sustainable finance in Germany and Denmark, we performed regression analyses on different strengths using the 2019 and 2020 data sets. The two-year study provides a temporal narrative, providing a comprehensive overview of the impact of energy sources on sustainable development in Germany and Denmark (Gunst & Mason, 2018).

4.2.4. ANOVA

ANOVA is used to evaluate the average variability in the regression and residual datasets. The objective is to detect statistically significant disparities in the influence of AI-powered green finance on investments in renewable energy, considering different categories and time intervals. Utilising ANOVA allows for the examination of the efficacy of tactics, and improving comprehension of the connection between green banking and beneficial outcomes (Potvin, 2020).

4.3. AI-Based Data Collected by Germany and Denmark

Germany and Denmark both significantly utilize various forms of renewable energy production, including wind power, biomass, solar power, and hydropower. The statistical data from various sources was collected using AI algorithms, indicating a deliberate transition towards contemporary technology for data gathering, filtering, and processing. The regression analysis, a fundamental component of our methodology, is provided as a technique for predictive modeling. AI algorithms are essential in predicting future trends by analyzing carefully gathered historical data. This represents a shift from previous methods of gathering data and emphasizes the current need for AI for more precise forecasts. In addition, AI technologies played a crucial role in performing statistical studies such as paired sample t-tests and ANOVA (Lücking, 2023).

5. RESULTS AND DISCUSSIONS

5.1. Denmark Statistics

5.1.1. Null Hypothesis (H_0)

There is no significant difference in the mean energy production for each energy source between the 2019 and 2020.

5.1.2. Alternative Hypothesis (H_1)

There is a significant difference in the mean energy production for each energy source between the 2019 and 2020 (Ruiz-Ruano García & López Puga, 2018).

Table III, displays the outcomes of a paired sample test, focusing on the disparity between values as a percentage of billion kWh for a particular pair. The average difference is -909.000 , with a measure of variability known as the standard deviation equal to 1106.275 and a measure of uncertainty known as the standard error of the mean at 349.835 . The 95% confidence interval for the difference is from -1700.381 to -117.619 . The t-statistic is -2.598 with 9 degrees of freedom, yielding a two-tailed significance value of 0.029 , suggesting a statistically significant distinction. These findings indicate that there is a high probability of substantial differences between the billion-kWh readings in the paired samples. Significance $0.029 < \alpha = 0.05$, which means reject the null hypothesis it indicates that there is evidence to suggest that the mean energy production for that particular renewable energy source is different between the two years (LePine, 2022).

H_0 : There is no significant linear relationship between “Energy Production in 2019” and “Energy Production in 2020”.

H_1 : There is a significant linear relationship between “Energy Production in 2019” and “Energy Production in 2020”.

The regression model is summarized in Table IV, which lists the variables that were included and excluded. Model 1 includes only the variable “billion kWh” and does not exclude any variables. The “Enter” method was utilized, indicating that all required variables were incorporated in the study, with the dependent variable being “Billion kWh.” This model configuration represents a regression study that focuses on a single variable.

5.1.3. Model Summary

A brief summary of the regression model’s performance is provided in Table V. A correlation coefficient (R) of 1.000 indicates that there is a perfect linear relationship between the predictor variable (billion kWh) and the dependent variable in Model 1. The model completely accounts for the dependent variable’s variability when both the R square and the adjusted R square yield a result of 1.000. The average dispersion of the data points from the regression line, or standard error of the estimate, comes to 466.866. According to Korberg et al. (2020), the change statistics show that the R square change, F change, and related degrees of autonomy are statistically significant. This suggests that the framework is well-fitted and has a very significant overall fit.

5.1.4. ANOVA

The ANOVA findings for Model 1, with the dependent variable “billion kWh,” are presented in Table VI. The regression phase presents a sum of squares of

TABLE IV: VARIABLES ENTERED/REMOVED^a

Model	Variables entered	Variables removed	Method
1	Billion kWh ^b	.	Enter

Note: a. Dependent Variable: Billion kWh.
 b. All requested variables entered.

TABLE V: MODEL SUMMARY

Model	R	R square	Adjusted R square	Std. error of the estimate	Change statistics				
					R square change	F change	df1	df2	Sig. F change
1	1.000 ^a	1.000	1.000	466.866	1.000	64326.719	1	8	0.000

Note: a. Predictors: (Constant), Billion kWh.

TABLE VI: ANOVA^a

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	14020929182.398	1	14020929182.398	64326.719	0.000 ^b
	Residual	1743714.502	8	217964.313		
	Total	14022672896.900	9			

Note: a. Dependent Variable: Billion kWh.
 b. Predictors: (Constant), Billion kWh.

TABLE VII: COLLINEARITY DIAGNOSTICS^a

Model	Dimension	Eigenvalue	Condition index	Variance proportions	
				(Constant)	Billion kWh
1	1	1.621	1.000	0.19	0.19
	2	0.379	2.070	0.81	0.81

Note: a. Dependent Variable: Billion kWh.

14,020,929,182.398 with 1 degree of freedom, yielding a median square price of 14,020,929,182.398. The F-statistic is 64326.719, and the p-value is .000, indicating a regression version. This is very extensive. The residual element shows the cumulative sum of squares for the residuals, whereas the whole section gives the overall cumulative sum of squares (Goldberg & Scheiner, 2020).

Model 1 with the based variable “Billion kWh” is described in Table VII, which includes diagnostics for collinearity. The regular and predictor variables “Billion kWh” are represented within the desk together with their corresponding dimensions, eigenvalues, circumstance indices, and variance proportions. The condition index and eigenvalues are useful tools for evaluating multi-collinearity, and the variance proportions show how much each variable contributes to the total variance. Both variables contribute equally to the variance in this case, and the values indicate a moderate degree of collinearity (Salmerón-Gómez et al., 2020).

Model 1’s coefficients using “billion kWh.” as the dependent variable are shown in Table VIII. A standard error of 188.450 is associated with the constant term, which is 145.168. The “billion kWh” predictor variable has a standard error of 0.004 and a coefficient of 1.026. Beta, the standardized coefficient, is equal to one thousand. “Billion kWh” has a t-statistic of 253.627 and a p-value of 0.000, both of which point to a very significant correlation.

The comparison of energy production in 2019 and 2020 of Denmark from different sources is shown in Fig. 1. The orange line represents production levels in 2019, while the

blue line depicts production levels in 2020. Both lines are measured in billions of kWh.

Table IX, displays the descriptive data for the variable “Billion kWh” in both the years 2019 and 2020. The dataset for the year 2019 consists of 14 observations. The range of the data is 602, with the maximum value also being 602. The mean of the dataset is 103.71, and the standard deviation is 157.232. The variance of the data points is 24721.758, which represents the extent of their dispersion. The skewness and kurtosis coefficients are 2.811 and 8.660, respectively, offering valuable information about the shape of the distribution. In 2020, the statistics indicate comparable patterns, with a range of 568, the highest number of 568, a mean of 99.64, and a standard deviation of 150.142. These figures provide essential data for the research, presenting a comprehensive analysis of the breakdown and fluctuation of energy output in both 2019 and 2020 (Siedlecki, 2020).

5.2. Germany Statistics

5.2.1. Null Hypothesis (H0)

There is no significant difference in the mean energy production for each energy source between the 2019 and 2020.

5.2.2. Alternative Hypothesis (H1)

There is a significant difference in the mean energy production for each energy source between the 2020 (Ruiz-Ruano García & López Puga, 2018).

Table X displays the outcomes of a paired samples test that is used to examine the differences between “billion

TABLE VIII: COEFFICIENTS

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
	B	Std. error				Tolerance	VIF
1 (Constant)	145.168	188.450		0.770	0.463		
Billion kWh	1.026	0.004	1.000	253.627	0.000	1.000	1.000

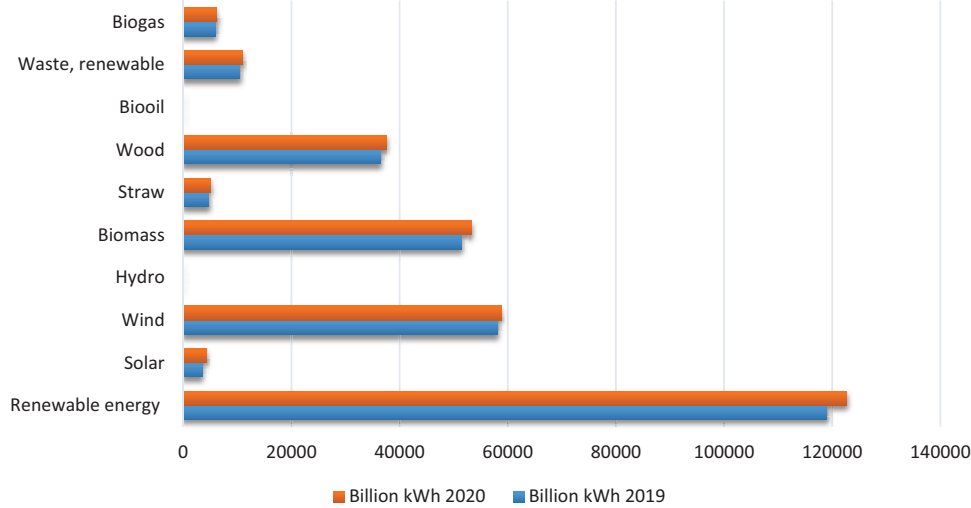


Fig. 1. Ratio of energy resources production in 2019 and 2020.

TABLE IX: DESCRIPTIVE STATISTICS

	N	Range	Maximum	Mean	Std. deviation	Variance	Skewness	Kurtosis		
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. error	Statistic	Std. error	
Billion kWh 2019	14	602	602	103.71	157.232	24721.758	2.811	0.597	8.660	1.154
Billion kWh 2020	14	568	568	99.64	150.142	22542.555	2.708	0.597	7.959	1.154
Valid N (listwise)	14									

kWh” values. A measure of the dispersion of the data from the mean is 12.162, and a measure of the potential for error in the mean difference is 3.250; the average difference is 4.071. From -2.951 to 11.094 is the range of the 95% confidence interval. The t-statistic, which is based on 13 degrees of freedom, is 1.253. As a result, the p-value with two tails is .232. According to these numbers, the matched samples of “Billion kWh.” do not differ significantly from one another. The null hypothesis is maintained because significance is $0.232 > \alpha = 0.05$. According to LePine (2022), there is no indication that the average energy output from that specific renewable source differs between the two years.

H-0: There is no significant linear relationship between “Energy Production in 2019” and “Energy Production in 2020”.

H-1: There is a significant linear relationship between “Energy Production in 2019” and “Energy Production in 2020”.

The factors that have been added and removed from Model 1 are described in Table XI.

Model 1 is succinctly summarized in Table XII. The correlation coefficient (R) is 0.998, indicating a highly robust linear relationship. The model accounts for 99.6 percent of the variation in the dependent variable, as shown by the R square and modified R square values of 996. The

standard error of the estimate is 10.046, which indicates the average amount by which observed data deviate from the regression line. The change statistics indicate a remarkably significant increase in R squared and F values, which supports the model’s strong fit and suggests a very low likelihood of occurring randomly (Pata et al., 2023).

Model 1’s ANOVA findings show a highly significant regression with the dependent variable “Billion kWh” (Table XIII). With 1 degree of freedom, the regression’s sum of squares is 291,842.223, giving a mean square value of the same amount. The 2891.934 F-statistic and corresponding p-value of .000 indicate a high level of general fit between the dependent variable and the regression model (Goldberg & Scheiner, 2020).

Coefficients for Model 1 with “billion kWh.” as the dependent variable are shown in Table XIV. With a margin of error of 3.254, the constant term is 0.810. The “Billion kWh” predictor variable is 0.953 with a 0.018 standard error. A beta value of 99.98 is used to normalize the coefficient. “Billion kWh” has a t-statistic of 53.777 and a p-value of 0.000, showing a strong and significant link. With a tolerance and VIF of 1.000, there are no concerns with the linearity statistics.

Model 1’s collinearity diagnostics with the dependent variable “Billion kWh” are presented in Table XV. The

TABLE X: PAIRED SAMPLES TEST

Pair 1	Billion kWh-billion kWh	Paired differences				t	df	Sig. (2-tailed)
		Mean	Std. deviation	Std. error mean	95% confidence interval of the difference			
					Lower Upper			
		4.071	12.162	3.250	-2.951 11.094	1.253	13	0.232

TABLE XI: VARIABLES ENTERED/REMOVED^a

Model	Variables entered	Variables removed	Method
1	Billion kWh ^b		Enter

Note: a. Dependent Variable: Billion kWh.
 b. All requested variables entered.

TABLE XII: MODEL SUMMARY

Table 5.11 Model summary									
Model	R	R square	Adjusted R square	Std. error of the estimate	Change statistics				
					R square change	F change	df1	df2	Sig. F change
1	0.998 ^a	0.996	0.996	10.046	0.996	2891.934	1	12	0.000

Note: a. Predictors: (Constant), Billion kWh.

TABLE XIII: ANOVA^a

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	291842.223	1	291842.223	2891.934	0.000 ^b
	Residual	1210.991	12	100.916		
	Total	293053.214	13			

Note: a. Dependent Variable: Billion kWh.
 b. Predictors: (Constant), Billion kWh.

TABLE XIV: COEFFICIENTS^a

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.	Collinearity statistics	
		B	Std. error				Beta	Tolerance
1	(Constant)	0.810	3.254		0.249	0.808		
	Billion kWh	0.953	0.018	0.998	53.777	0.000	1.000	1.000

Note: a. Dependent Variable: Billion kWh.

constant and predictor variable “Billion kWh.” are represented in the table together with their corresponding dimensions, eigenvalues, condition indices, and variance proportions. The results indicate a modest degree of collinearity, with both variables accounting for about the same amount of variance (Salmerón-Gómez et al., 2020).

The difference in Germany’s energy production from 2019 to 2020 is seen in Fig. 2. Both lines represent production levels in billions of kWh; the orange line represents 2019 levels, while the blue line represents 2020 levels.

The variable “billion kWh” is descriptively shown in Table XVI for the years 2019 and 2020. Fourteen observations make up each dataset. In 2019, there is a standard deviation of 157.232 units, a mean of 103.71, and a range of 602 units. There appears to be some variation in the data, as the variance is 24721.758. Skewness (2.811) and kurtosis (8.660) are likely indicators of an unusual distribution. The data from 2020 shows similar patterns, which help us,

understand the distribution and volatility of “billion kWh” for those two years (Siedlecki, 2020).

5.3. AI-Driven Based Results Germany and Denmark

Fig. 3 visually depicts Germany’s green energy production from 1990 to 2022, highlighting the continuous and significant output levels. The graph illustrates the yearly evolution from 1990 to 2022, displaying production levels that vary from 0 to 60,000 GWh. More precisely, it clarifies the relative contribution of different renewable energies to total energy production. Significantly, biogases have emerged as a prominent feature, demonstrating a consistent focus on utilizing this specific renewable source for generating electricity. This conclusion is consistent with our extensive research on AI-powered sustainable finance initiatives in Germany. The graph demonstrates a systematic and well-informed strategy for utilizing biogases for renewable energy investments. AI optimization was a key part of finding and improving biogases’ future potential. This shows how technological advances are strategically

TABLE XV: COLLINEARITY DIAGNOSTICS^a

Model	Dimension	Eigenvalue	Condition index	Variance proportions	
				(Constant)	Billion kWh
1	1	1.565	1.000	0.22	0.22
	2	0.435	1.896	0.78	0.78

Note: a. Dependent Variable: Billion kWh.

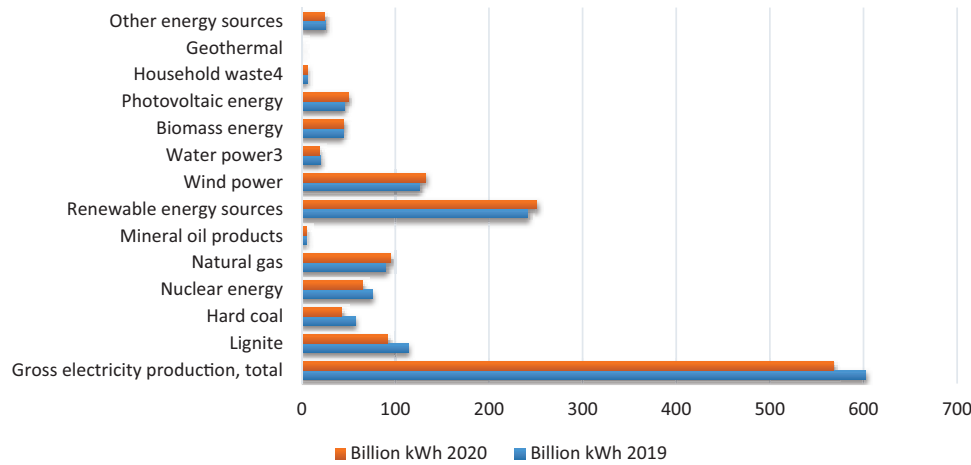


Fig. 2. Ratio of renewable energy sources in Germany (2019 and 2020).

TABLE XVI: DESCRIPTIVE STATISTICS

	N	Range	Maximum	Mean	Std. deviation	Variance	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. error	Statistic
Billion kWh 2019	14	602	602	103.71	157.232	24721.758	2.811	8.660
Billion kWh 2020	14	568	568	99.64	150.142	22542.555	2.708	7.959
Valid N (listwise)	14							

linked with goals for sustainable energy. This enhances the dependability of Germany’s renewable energy industry and validates the beneficial influence of AI-driven methods in creating and maintaining environmentally friendly initiatives (Bórawski et al., 2019).

Fig. 4 illustrates the proportion of clean energy resource production in Denmark from 1990 to 2022, displaying the yearly output in gigawatt-hours (GWh), with values ranging from 0 to 10,000 GWh. Denmark’s dedication to utilizing AI methods is particularly apparent in our research, focusing specifically on the years 2019 and 2020. Denmark utilized AI technologies to enhance its energy production, with a focus on achieving accuracy in data collection. The diagram depicts the profound influence of artificial intelligence, showcasing the correlation between Denmark’s focus on precise data gathering and the significant increase in energy generation. Upon analyzing the image, it is evident that primary solid biogas plays a central role as a significant renewable energy source for electricity generation in Denmark. This discovery is directly relevant to our study’s emphasis on AI-powered techniques used in Denmark for sustainable finance. The focus on robust biogas signifies a deliberate synchronization of AI technology with Denmark’s objectives in the field of sustainable energy.

5.4. Discussions

The research delves into the intricacies of renewable energy investments in both European countries. By examining large data sets, doing statistical evaluations, and performing regression analysis, we can obtain valuable insights into the impact of AI-driven policies on sustainable development. Denmark underwent a substantial change in average energy output from 2019 to 2020, as indicated by an important paired sample t-test. The regression model demonstrates a robust correlation between the predicted variable “billion kWh” and energy production, indicating a perfect linear relationship. The results emphasize the ever-changing characteristics of Denmark’s energy environment, necessitating flexible planning approaches. Integrating AI technologies for optimization is essential for synchronizing energy output with changing demands. In contrast, the paired sample t-test conducted in Germany did not reveal a statistically significant difference in the average energy production between the years 2019 and 2020. Nevertheless, the regression model, which is very significant, accounts for 99.6% of the variation and indicates a fairly consistent energy production environment. Germany’s reliable energy generation is in line with enduring policy stability, fostering an atmosphere that promotes sustainable development. The visual depictions of AI-generated outcomes demonstrate the progress of renewable energy generation in both nations. The emphasis on biogas as a substantial renewable energy resource

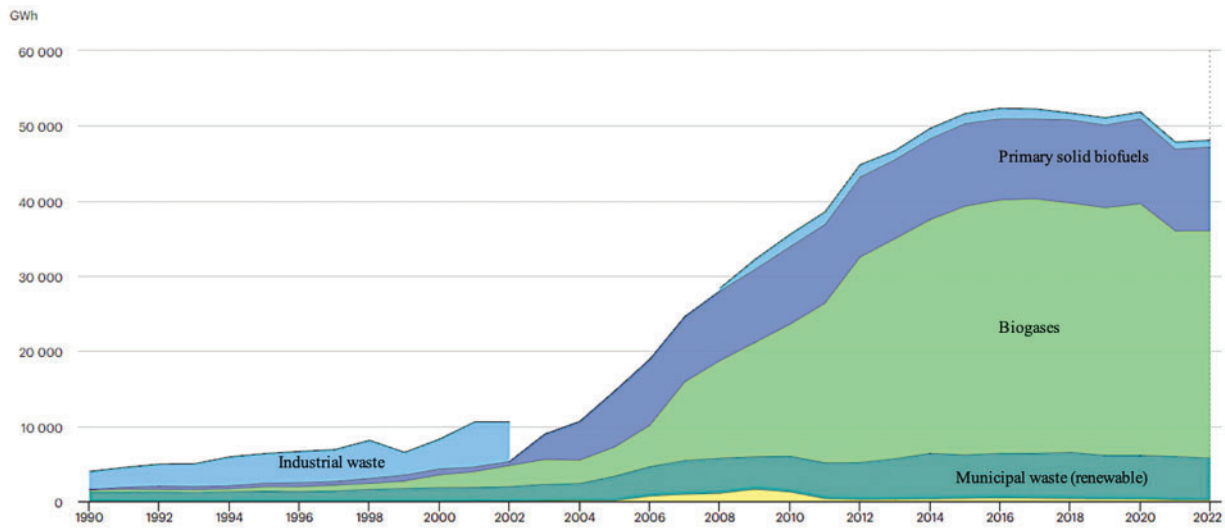


Fig. 3. Electricity generation from biofuels and waste by source, Germany 1990–2022.

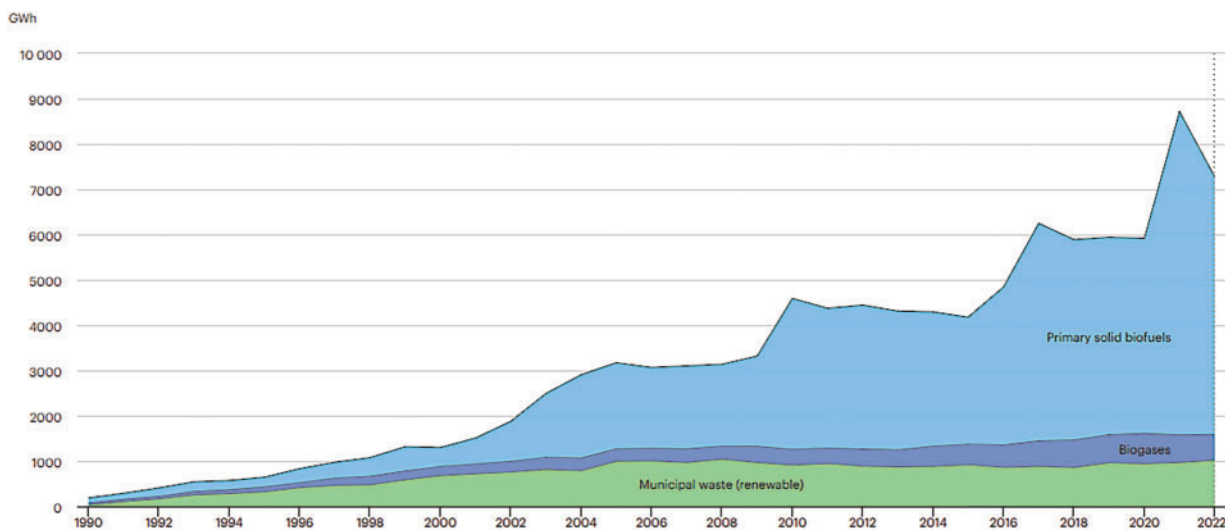


Fig. 4. Electricity generation from biofuels and waste by source, Denmark 1990–2022.

corresponds with sustainable finance endeavours. Both countries strategically utilized AI technologies, emphasizing the significance of accuracy in data gathering and the prioritization of renewable energy sources. The focus of both countries on biogas and the accuracy provided by AI in data gathering contribute to sustainable and environmentally conscious energy planning. These findings provide useful insights for future studies investigating the dynamic relationship between AI technology and financial sustainability initiatives on a worldwide level.

6. CONCLUSION

This assertion acknowledges the significance of the global reputation for environmentally sustainable roles and the crucial role of AI in facilitating the digital transformation in green finance. The background component situates the research within modern-day financial and economic boom frameworks stimulated by the modernization principle and AI era, acknowledging the splendid difficulties presented by international environmental degradation and climate trade. The motivation segment highlights the

pivotal function of the banking area in mitigating international warming, emphasizing the importance of digital innovation in achieving sustainable development and curtailing greenhouse gas emissions. AI integration into the inexperienced economic system is considered essential for shaping monetary alternatives and selling sustainability.

The comparative research emphasizes the crucial importance of AI-driven tactics in effectively navigating the intricacies of investments in renewable energy. AI technologies are essential for promoting sustainable growth, whether it is through navigating through changing landscapes in Denmark or ensuring stability in Germany. These findings enhance our comprehension of the energy flows in these European nations and provide vital insights for worldwide endeavours in designing ecologic and renewable energy futures. As we approach significant changes, the incorporation of AI technology becomes a fundamental element in guiding nations towards a more environmentally friendly and enduring future. This emphasizes the importance of future research that aims to solve these limitations. The following sections provide a comprehensive examination of the literature, theoretical framework,

methodology, and outcomes, providing useful perspectives on the incorporation of AI-powered green finance methods for sustainable development.

CONFLICT OF INTEREST

The authors declare that they do not have any conflict of interest.

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