Impact of Artificial Intelligence, ICT, and Technological Innovations on Informational Energy System: A Quantile Varying Effect of Using Methods of Moments Quantile Regression (MMQR)

Bo Yu

Recommended citation:

Yu, Bo (2024). "Impact of Artificial Intelligence, ICT, and Technological Innovations on Informational Energy System: A Quantile Varying Effect of Using Methods of Moments Quantile Regression (MMQR)". *Profesional de la información*, v. 33, n. 5, e330509.

https://doi.org/10.3145/epi.2024.0509

Manuscript received on 11th December 2023
Accepted on 19th October 2024

Bo Yu
https://orcid.org/0009-0006-3248-6449
School of Economics
Hunan Institute of Engineering
Xiangtan, Hunan 411104, China
yubo197606@126.com

Abstract

The growing contribution of artificial intelligence into several domains, including environmental sustainability and informational energy, has gained dramatic attention from several stakeholders. This research investigates the impact of artificial intelligence, information and communication technologies (ICTs), and technological innovations on information energy systems, with respect to environmental sustainability and economic growth of China. Data was collected during 2001-2020 with yearly observations. The study applied the Methods of Moments Quantile Regression (MMQR) to examine the quantile varying trend of information energy as determined by the stated variables. The results through the MMQR estimator show that artificial intelligence boosts information energy from the 0.25th to 0.90th Quantile, where the highest effect is observed at the 0.75th Quantile. The results also show a positive connection between ICT and information energy across all the quantiles. Moreover, technological innovations positively impact the information energy from 0.75th to 0.90th Quantile. Conversely, environmental sustainability hinders such energy production across all the quantiles. Finally, our findings confirm the productive effect of economic growth in determining an increasing trend of information energy. The study provides several policy suggestions while considering all of the given variables. Besides, the limitations are also highlighted by the end of this research to demonstrate the directions for future studies.

1. Introduction

Artificial Intelligence (AI) and digital technology play a key role in advancing information and communication technologies (ICTs) and technological innovations. AI also offers powerful solutions for environmental sustainability such as reducing pollution and minimizing waste. This combination of AI and digitalization is essential in promoting more sustainable future (**Apergis *et al.***, 2023; **Pata; Aydin**, 2020). AI enhances the development of renewable resources; it not only accelerates the energy in the information technology but also makes entire energy more sustainable. While AI plays a central role in minimizing carbon emissions, it also helps in mitigating challenges in energy storages. According to Innovation for Cool Earth Forum (ICEF), AI is transforming several key areas of energy. Its revolutionizes these areas from solar radiation, wind power, wind wave weather prediction, load balancing, and risk identification, making the whole system sustainable (**Sandalow *et al.***, 2023). Information and Communication Technology (ICT) is equally important in protecting the environment, as it can potentially impact its sustainability (**Shah *et al.***, 2022). Some scholars have found that ICT has a strong impact on energy systems. It allows energy managers to analyze energy data in time (**Balsalobre-Lorente *et al.***, 2023; **Taneja; Mandys**, 2022). Technological innovation, too, plays a vital role in advancing the renewable resources. In essence, technological innovation is the backbone of energy, making it more efficient (**Aydin; Bozatli**, 2023).

The current research investigates the interlinkages between the artificial intelligence, information and communication technologies, and technological innovations in the context of environmental sustainability, informational energy systems, and economic growth of the Chinese economy, which seems to be in dearth in the scholarly debate till date. This study is expected to be a groundbreaking study that examines the relationships between the explained variables of interest using the MMQR estimation technique, which helps to distribute the primary dependent variable over lower, middle and higher-order quantiles. The given distribution provides a better understanding of the trends in the primary outcome variable.

2. Literature Review

The growing energy demand worldwide is a big challenge, causing environmental challenges (**Krishnan *et al.***, 2021). The current energy system, which relies heavily on fossil fuels like coal, oil, and gas, impacts the economy and the environment (**Simon**, 2024). Energy sources like coal, oil, and gas threaten sustainable development because they harm the environment (**Khan; Liu**, 2023). If things continue as they are, the world's energy increase by about 1.2% each year until 2035 (**Tanaka**, 2010). In such as state, artificial intelligence, information and communication technologies (ICTs), and technological innovations will ensure the environmental sustainability and maintenance of informational energy systems or green energy. More specifically, the information energy management seeks to improve the efficiency of IT operations, while ICTs focus on generating energy from sustainable sources. Therefore, with an increasing demand for the sustainability outlook, the governments around the globe need to spend more money and focus on environmental sustainability and information energy management. The economies like China, the EU, the UK, and the US are encouraging the use of information energy management by creating policies that support efficient information energy generation within the ICT environment. By doing this, they are helping to change the climate and clean the environment as it will reduce the use of toxic equipment and resources. Without support from the government, it is challenging for companies to act in a friendly manner to the environment. Making policies or rules from companies makes it easier to adopt green technologies and reduce environmental pollution (**Abakah *et al.***, 2023).

In addition, the IT energy management faces many challenges, including the need for a consistent power supply to maintain optimal system performance. Fluctuations in energy availability can lead to system outages and performance issues, making it difficult for organizations to rely on their IT infrastructures, hence leading towards more energy related concerns. Moreover, factors such as energy fluctuations, load management, cyber-attacks, and infrastructure controls are much crucial to be considered as they can complicate the reliable use of information energy management. Additionally, managing energy in field of information technology is influenced by equipment efficiency and operational demands. For instance, a sudden spike in demand can strain the system and lead to energy shortages. Meanwhile, it is also observed that weather factors like temperature and humidity also impact the performance of data centers, increasing cooling needs and energy consumption. Fluctuating operational demands throughout the day and across seasons create unstable energy consumption patterns, drive up costs and complicate energy efficiency efforts. Besides, during the peak usage times, companies may need to rely on more expensive energy sources to maintain performance, further complicating budget management.

Additionally, many people are concerned about turbines, such as their size, noise, the lights they use at night, and how they can harm the animals and birds (**Kirkegaard *et al.***, 2023). These challenges can be reduced by using artificial intelligence (AI) (**Allison *et al.***, 2019). So, AI plays a key role in increasing green production. AI is a type of advanced technology that focuses on creating smart machines that help to solve problems and make the system renewable (**Sarker**, 2022), according to (**Sheikh *et al.***, 2023). AI refers to the computer systems that can observe their environment, analyze data, and make decision on their own to achieve the goals. AI plays a vital role in improving the energy (**Hannan *et al.***, 2021). According to **Zhang *et al.*** (2021), using AI to improve the wind energy system can make it more reliable. These systems combine wind energy with hydrogen energy systems to provide powerful impacts. AI can also analyze data, manage the energy flow and reduce waste from the system smoothly (**Stanford University**, 2023). AI can also detect the problems in energy system and ensuring that everything runs smoothly. This leads to more efficient Renewable and Alternative Energy Systems (RAES) operation, like solar and wind power. By improving these systems, AI is paving the way for the future and can manage energy needs automatically (**Hatti; Denai**, 2020). AI can effectively manage different parts of hybrid energy systems, like solar panels and wind turbines. This system also helps to get more energy from the sun and wind. AI also encourages the growth and improvement of these energy technologies (**Zahraee *et al.***, 2016). AI can help make information technology systems more efficient. The combination of AI and IT energy management supports the environmental balance on the earth and promotes more sustainable future (**Vinuesa *et al.***, 2020). This strengthening policy encourages the use of clean energy on worldwide, as more countries adopt cleaner energy sources and reduce fossil fuels for combat climates (**Yuksel; Kaygusuz**, 2011).

Furthermore, ICT analyses data in time to allow energy managers to use energy during peak production times. It also helps them to decide when energy is stored for future use. Using fossil fuels and non-renewable resources for energy production can harm the Earth's natural resources. Non-renewable energy like coal and oil limit resources and worsen environmental problems like global warming and water shortages (**Huang *et al.***, 2020). In middle-income countries, natural resources play a significant role in the use of biomass energy. However, it is essential to realize that these resources also shape energy consumption. To reduce emissions, middle-income countries need to move away from fossil fuels and use more clean energy, but they'll need to invest in new technologies by using their natural resources wisely (**Naqvi *et al.***, 2023).

Table 1 summarizes a few past studies in terms of their variables, methods used and results. The objective of putting all these studies together is to make a comparison of these studies to determine how past research has dealt with the variables under the current study.

Table 1: Past Studies, their Authors and Variables in the Present Context.

Authors	Variables	Methods	Region	Short Results
(**Hammerschmitt *et al.***, 2022)	Electrical energy generation capacity, Energy complementarity, Historical operation series, Hydro and wind generation	Multi-layer Perceptron (MLP) artificial neural networks, Monte Carlo (MC) method	Not specified	Mean absolute error: 3.22% for hydro generation, 5.36% for wind generation; RMSE: 4.01% for hydro generation, 6.31% for wind generation.
	Generation forecasting, Energy complementarity, Available thermal generation, Simulated thermal generation, System load	Simulation, Monte Carlo scenarios (critical, ideal, optimistic)	Not specified	Possible to estimate complementary and simulated natural gas thermal generation to meet system load; Aided in planning and operation of electrical systems.
(**Hammerschmitt *et al.***, 2022)	Sustainable and renewable energy, AI applications, Solar power, Photovoltaics, Microgrid integration, Energy storage, Wind, Geothermal energy	Review of more than 150 research reports from various databases	Not specified	Wide range of AI applications in solar, wind, geothermal, energy storage, and power management.
	Technological advances, Research outcomes, AI in renewable energy systems, Case studies, Challenges and solutions	Comprehensive analysis of AI approaches in renewable energy innovations	Not specified	Discussion on technological advances, potential challenges, solutions, and future trends for AI in renewable energy.
(**Rasheed *et al.***, 2024)	AI integration, Renewable energy production, Robotics, Environmental quality, Economic growth, ICT, Natural resources	Panel NARDL analysis, Country -specific investigation (Austria , Germany, New Zealand)	22 leading robotics and innovative countries	AI significantly stimulates renewable energy in the long-run; Both positive and negative AI shocks improve clean energy structure.
	AI shocks (positive and negative), Renewable energy stimulation, Asymmetric and symmetric assumptions	Panel symmetric ARDL analysis	Austria, Germany, New Zealand	Natural resources, ICT, and economic growth enhance renewable energy production; Affirmative and adverse AI changes impact Austria, Germany, and New Zealand in the short run.
(**Verma *et al.***, 2024)	AI applications, Energy supply chains, Trade, Renewable energy (wind, solar, geothermal, ocean, hydrogen storage), CO2-neutral hydrogen production	Review of AI-based energy management approaches, Comparison of AI efforts in the energy sector	Not specified	AI as a key enabler for renewable energy growth (wind, solar, hydrogen storage); Discussion of future research, energy efficiency, and policy.
	Energy management, Predictive maintenance, Energy efficiency optimization, AI efforts and applications, Policy making for renewable energy	AI tools for energy supply and demand management, Predictive maintenance control, Policy analysis	Not specified	Observations on AI efforts, energy management, challenges, and potential enhancements for renewable energy systems.
(**Xie *et al.***, 2024)	Natural resources, CO2 emissions, ICT, Foreign Direct Investment (FD), Renewable energy	Nonlinear Autoregressive Distributive Lag (NARDL) methodology, Causality analysis	China	Positive shocks in natural resources reduce CO2 emissions; Negative shocks increase CO2 emissions.
	Natural resources shocks (positive and negative), CO2 emissions, ICT, FDI	Empirical investigation over 31 years (1990-2021)	China	ICT and FDI contribute to rising CO2 emissions; Renewable energy adoption is essential to mitigate emissions.
(**Solarin *et al.***, 2022)	Renewable energy innovation, Renewable energy production, Green growth, GDP, Producer Price Index, CO2 emissions	Panel quantile regression augmented with the method of moments	BRICS countries (Brazil, Russia, India, China, South Africa)	Renewable energy innovation positively impacts renewable energy production across all quantiles.
	Impact of renewable energy innovation on renewable energy production, GDP, CO2 emissions	Empirical investigation from 1993 to 2018	BRICS countries (Brazil, Russia, India, China, South Africa)	Countries with smaller renewable energy production per capita experience a greater impact from innovation
(**Vural**, 2021)	GDP per capita, CO2 emissions per capita, Technological innovation, Trade, Renewable energy production	Panel estimation methods, Pedroni and Westerlund panel cointegration tests	Latin American countries (Argentina, Brazil, Mexico, Colombia, Chile, Guatemala)	GDP per capita, technological innovation, and trade positively impact renewable energy production.

3. Research Methods

Table 2 presents the variables, their nature and given time duration of the study.

Table 2: Variables and Measurement.

Variable	Nature	Time Duration
• Information Energy (INE) Systems	DV	2001-2020
• Artificial Intelligence (AIN)	IV	
• Information And Communication Technologies (ICTs)	IV	
• Technological Innovations (TI)	IV	
• Environmental Sustainability (ES)	Control	
• GDP/ Economic Growth	Control	

As explained earlier, this research aims to examine the quantile varying effect of the given explanatory variables on the main dependent variable which is information energy in the context of China. Therefore, this study collected annual observations from different online sources as provided in Table 1. However, before applying the valid statistical estimation techniques, it is imperative to explore the data trends using descriptive statistics regarding central tendency and measure of dispersions. For central tendency, the mean or average trend of the variables provides a good judgement to check the average points of the data for the given variables. Conversely, the dispersion measurement explores the deviation from the mean with the help of standard deviation and similar other measures. The minimum and maximum data points also provide the lowest and highest data trends. In the next step of the estimation, this research examined the collinearity concern by using the variance inflation factor (VIF) and tolerance values as denoted by one divided by VIF (**O'brien**, 2007; **Thompson *et al.***, 2017; **Salmerón Gómez *et al.***, 2016). The VIF and tolerance level findings are well captured in the subsequent analysis and discussion section. Consequently, this research has applied the Methods of Moments Quantile Regression (MMQR) to examine the Quantile varying effect in the main dependent variable, information energy, as determined by the set of explanatory and control variables. The applied technique of MMQR is widely suggested in the modern literature (**Yu *et al.***, 2023; **Kamran *et al.***, 2024; **Hassan**, 2023).

The baseline equation for exploring the relationships between these variables is as follows:

$$INE = f\,(AIN, ICT, TI, ES, GDP) \quad \text{Equation 1}$$

$$INEt = \beta 0 + \beta 1AINt + \beta 2ICTt + \beta 3TIt + \beta ESt + \beta 5GDPt + \mu_t \quad \text{Equation 2}$$

Equations 1 and 2 above reflect the INE, AIN, ICT, TI, ES, and GDP for the given outcome, as well as explanatory and control variables. In the second equation, the term U reflects the error terms for which other factors are not included in the model. For considering the MMQR, relevant Equations are as follows:

$$Q_{0.25}(INE_t) = \lambda_{0.25} + \beta_{1,0.25}AIN_t + \beta_{2,0.25}ICT_t + \beta_{3,0.25}TI_{t+}\ \beta_{4,0.25}ES_t + \beta_{5,0.25}GDP_t + \mu_{0.25} = \text{Equation 3}$$

$$Q_{0.50}(INE_t) = \lambda_{0.50} + \beta_{1,0.50}AIN_t + \beta_{2,0.50}ICT_t + \beta_{3,0.50}TI_{t+}\ \beta_{4,0.50}ES_t + \beta_{5,0.50}GDP_t + \mu_{0.50} = \text{Equation 4}$$

$$Q_{0.75}(INE_t) = \lambda_{0.75} + \beta_{1,0.75}AIN_t + \beta_{2,0.75}ICT_t + \beta_{3,0.75}TI_{t+}\ \beta_{4,0.75}ES_t + \beta_{5,0.75}GDP_t + \mu_{0.75} = \text{Equation 5}$$

$$Q_{0.90}(INE_t) = \lambda_{0.90} + \beta_{1,0.90}AIN_t + \beta_{2,0.90}ICT_t + \beta_{3,0.90TI}TI_{t+}\ \beta_{4,0.90}ES_t + \beta_{5,0.90}GDP_t + \mu_{0.90} = \text{Equation 6}$$

4. Results and Discussion

The data trends are reported using the descriptive statistics in Table 3, as annual observations for the past 20 years spanning between 2001-2020. The mean trend for the information energy has been negative, whereas for the rest of the variables, the highest value is linked with artificial intelligence as 7.84. Moreover, the lowest mean score is 0.453, related to Environmental sustainability. The deviation from the mean is the highest for information energy and artificial intelligence and lowest for the rest of the variables. In terms of minimum and maximum values linked with the variables, we found that GDP has a minimum score of 3.022 which is higher than other variables, and the same is the case for the maximum trend of the GDP, which is 4.017 during the study period.

Table 3: Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
INE	20	-3.365	1.904	-5.9	.1
AIN	20	7.84	1.109	6.2	10
ICT	20	1.289	.487	.249	1.807
TI	20	.737	.045	.651	.788
ES	20	.453	.319	-.064	.984
GDP	20	3.61	.347	3.022	4.017
Note: INE- information energy, AIN- artificial intelligence, ICT- information and communication technologies, TI- technological innovations ES- Environmental sustainability, GDP- gross domestic product					

The investigation for the collinearity between the variables named artificial intelligence, information and communication technologies, Technological innovation, Environmental sustainability, and GDP (economic growth) are well covered in Table 4 by providing variance inflation factor and relative tolerance scores. It has been observed that INE, AIN, ICT, TI, ES, and GDP as 2.78, 2.652, 1.632, 3.85, 1.2, and 3.61. These scores are less than 5, a normal threshold level of VIF as recommended (**Kalnins; Praitis Hill**, 2023; **O'brien**, 2007; **Ye *et al.***, 2022). Similarly, the tolerance values for these variables are 0.355, 0.377, 0.613, 0.260, 0.833, and 0.277, which are higher than 0.10. As the VIF and 1/VIF cover the fact that none of these variables show any concern related to higher correlation, the study has finalized their role as key predictors of information energy from the context of China.

Table 4: Collinearity Analysis.

Variables	VIF	1/VIF
INE	2.78	0.355
AIN	2.652	0.377
ICT	1.632	0.613
TI	3.85	0.260
ES	1.2	0.833
GDP	3.61	0.277
Mean VIF	2.59	.
Note: INE- Information energy, AIN- artificial intelligence, ICT- information and communication technologies, TI- technological innovations ES- Environmental sustainability, GDP- gross domestic product		

As stated earlier, one of the primary contributions of this paper is to apply the MMQR estimation technique which help to explores different quantiles of the dependent variable, information energy, as predicted by set of explanatory and control variables. Table 5 to Table 8 present the 25^{th} , 50^{th}, 75^{th} and 90^{th} percentile respectively. Each percentile shows the locations and scales output to explore the position or central tendency for the conditional Quantile of the dependent variable, as well as slope coefficients in the quantile regression estimation, in Section A and B. However, the output shown in Section-C of each percentile would help to infer the positive connection between INE, AIN, ICT, TI and ES in achieving sustainable economic outcomes (GDP) in the regional context of China.

Table 5: MMQR Estimations (0.25^{th} Quantile).

Section-A: Location				
Variable	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	.0882***	0.071	13.25	0.000
AIN	1.098***	0.070	15.65	0.000
ICT	0.822**	0.367	2.24	0.025
TI	0.219 not significant	0.418	0.52	0.601
ES	-0.493***	0.122	-4.04	0.000
GDP	2.530***	0.662	3.82	0.000
_cons	-21.022***	1.445	-14.55	0.000
Section-B: Scale				
Variable	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	0.011 not significant	0.130	0.14	0.234
AIN	0.017 not significant	0.038	0.45	0.653
ICT	0.038 not significant	0.200	0.19	0.849
TI	-0.285 not significant	0.228	-1.25	0.210
ES	-0.007 not significant	0.066	-0.11	0.911
GDP	0.332 not significant	0.360	0.92	0.356
_cons	0.253 not significant	0.786	0.32	0.747
Section-C: Coefficients for 25th Quantile				
Variable	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	1.000***	0.071	12.64	0.000
AIN	1.085***	0.073	14.96	0.000
ICT	0.851**	0.378	2.25	0.025
TI	0.434 not significant	0.442	0.98	0.327
ES	-0.488***	0.126	-3.88	0.000
GDP	2.279**	0.692	3.29	0.001
_cons	-21.213***	1.492	-14.22	0.000
Note: INE- Information energy, AIN- artificial intelligence, ICT- information and communication technologies, TI- technological innovations ES- Environmental sustainability, GDP- gross domestic product				

Table 6: MMQR Estimations (0.50^{th} Quantile).

Section-A: Location				
Variable	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	1.023***	0.056	12.65	0.000
AIN	1.098***	0.070	15.65	0.000
ICT	0.822**	0.367	2.24	0.025
TI	0.219 not significant	0.418	0.520	0.601
ES	-0.493***	0.122	-4.04	0.000
GDP	2.530***	0.662	3.82	0.000
_cons	-21.022***	1.445	-14.55	0.000
Section-B: Scale				
Variable	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	0.002 not significant	0.012	0.25	0.445
AIN	0.017 not significant	0.038	0.45	0.653
ICT	0.038 not significant	0.200	0.190	0.849
TI	0.285 not significant	0.228	1.25	0.21
ES	-0.007 not significant	0.066	-0.11	0.911
GDP	0.332 not significant	0.360	0.92	0.356
_cons	0.253 not significant	0.786	0.32	0.747
Section-C: Coefficients for 50th Quantile				
Variable	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	1.561***	0.045	12.16	0.000
AIN	1.085***	0.073	14.96	0.000
ICT	0.851**	0.378	2.25	0.025
TI	0.434 not significant	0.442	0.98	0.327
ES	-0.488***	0.126	-3.88	0.000
GDP	2.279***	0.692	3.29	0.001
_cons	-21.213***	1.492	-14.22	0.000
Note: INE- Information energy, AIN- artificial intelligence, ICT- information and communication technologies, TI- technological innovations ES- Environmental sustainability, GDP- gross domestic product				

Table 7: MMQR Estimations (0.75th Quantile).

Section-A: Location				
Location	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	1.012	0.045	12.67	0.000
AIN	1.098	0.070	15.65	0.000
ICT	0.822	0.367	2.24	0.025
TI	0.219	0.418	0.52	0.601
ES	-0.493	0.122	-4.04	0.000
GDP	2.530	0.662	3.82	0.000
_cons	-21.022	1.445	-14.55	0.000
Section-B: Scale				
Scale	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	0.034	0.023	0.24	0.145
AIN	0.017	0.038	0.45	0.653
ICT	0.038	0.200	0.19	0.849
TI	0.285	0.228	1.25	0.21
ES	-0.007	0.066	-0.11	0.911
GDP	0.332	0.360	0.92	0.356
_cons	0.253	0.786	0.32	0.747
Section-C: Coefficients for 75th Quantile				
Quantile	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	1.234***	0.025	11.24	0.000
AIN	1.116***	0.085	13.13	0.000
ICT	0.783*	0.444	1.76	0.078
TI	0.178***	0.011	16.181	0.000
ES	-0.501***	0.148	-3.39	0.001
GDP	2.876***	0.806	3.57	0.000
_cons	-20.759***	1.751	-11.86	0.000
Note: INE- Information energy, AIN- artificial intelligence, ICT- information and communication technologies, TI- technological innovations ES- Environmental sustainability, GDP- gross domestic product				

Table 8: MMQR Estimations (0.90th Quantile).

Section-A: Location				
Location	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	0.225***	0.134	3.85	0.000
AIN	0.635***	0.131	4.85	0.000
ICT	0.732***	0.127	5.77	0.000
TI	0.219 not significant	0.418	0.52	0.601
ES	-0.593***	0.122	-4.86	0.000
GDP	1.530***	0.362	4.22	0.000
Section-B: Scale				
Scale	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	0.174***	0.037	2.502	0.000
AIN	0.172***	0.038	4.502	0.000
ICT	0.138***	0.040	3.482	0.000
TI	0.285***	0.019	3.130	0.000
ES	-0.007 not significant	0.066	-0.112	0.911
GDP	0.132***	0.010	12.854	0.000
_cons	0.253 not significant	0.786	0.322	0.747
Section-C: Coefficients for 90th Quantile				
Quantile	**Coef.**	**S.E**	**Z-value**	**P-value**
INE	1.145**	0.034	9.777	0.000
AIN	1.112***	0.095	11.705	0.000
ICT	0.617***	0.144	4.284	0.000
TI	0.138***	0.011	12.754	0.000
ES	-0.401***	0.124	-3.240	0.000
GDP	2.159***	0.306	7.067	0.000
_cons	-10.169***	1.751	-5.808	0.000
Note: INE- Information energy, AIN- artificial intelligence, ICT- information and communication technologies, TI- technological innovations ES- Environmental sustainability, GDP- gross domestic product				

The location and scale's output for the 25th Quantile is well presented in Sections A and B of Table 5. Both the locations and scales output help explore the position or central tendency for the conditional Quantile of the dependent variable, as well as slope coefficients in the quantile regression estimation. However, our main concern is related to the output shown under Section-C in Table 5, for each of the quantiles. The findings under 25th Quantile show that the coefficient for artificial intelligence in determining the information energy is positive and significant. More specifically, the coefficient shows that keeping the rest of the factors constant, a one percent upsurge in the AIN is causing to an upwards shift in the INE by 1.085, respectively. This impact is significant at 1% and showing 99% confidence level at ***. The observed effect of the AIN on the INE has several mechanisms to be explored. Considering the relationship between artificial intelligence, information and communication technologies (ICTs), technological innovations and information energy, the findings provide some mixed results. For example, under the 25th Quantile, the TI's efficiency is 0.434, showing a higher standard error, while leading to a lower t-statistics and higher p-value. Consequently, the impact of the TI on INE has been found as positive but insignificant with reference to other higher order percentile.

For instance, the effect of TI on INE for the 50th Quantile is positive and insignificant, confirming what was observed for the 25th Quantile. However, for the 75th Quantile, the coefficient for the TI is 0.178 with the significant p-value at 1%. It means that keeping all of the other factors as constant, an increasing trend in technical innovations in China tend to increase the generation of the clean energy by 0.178% during the past two decades. The Chinese government also plays an active part by encouraging these innovations, specifically in the area of informational energy. It provides financial incentives like research funding, tax breaks, and support for bringing these technologies to market. Such acts create a favorable environment for continuous advancements in the informational energy management system. Meanwhile, the Chinese economy has been emerged as a top player in the energy industry. With an increasing number of patents to mark technological innovations, Chinese companies and similar organizations have gained a competitive edge in the global context by exporting green technologies and pushing forward the adoption of IT energy management at the domestic market. Therefore, a positive relationship between the increasing level of technological innovations and information energy is vital.

The same positive effect of the AIN on the INE has been found under the 0.50th to 90th quantiles; however, the direction of the coefficients is the same but with different magnitudes. For example, the 0.50th Quantile's coefficient is 1.085, whereas for the 0.75th and 0.90th, the coefficients are 1.116 and 1.112, respectively. All of these values are confirming the productive effect of the AIN in promoting the information energy for the Chinese economy during 2000-2020. As observed in past studies, AIN had the potential to promote advancements. Moreover, AIN played a pivotal role in fostering the development of innovative methods that create efficient ways to manage and utilize information energy. Therefore, achieving the goals related to effective information energy management depends on effectively applying AIN and making breakthroughs in the entire information systems infrastructure. Additionally, AIN tends to forecast and optimize system designs for maximum efficiency and effectiveness in information energy management. In this regard, the study conducted by **Vyas *et al.*** (2022) has integrated AI into information systems and shows that artificial intelligence can significantly help protect resources and enhance management practices.

Research conducted by **Zhang *et al.*** (2022) supports the idea that AI technologies have successfully addressed the challenges linked with integrating and improving the energy system. It has also been explained that economies like the US, and China have gained a competitive position in becoming the leaders for industrial automation). As a result, such leadership has paved the way for the efficient use of AIN in sustainable energy strongly supporting artificial intelligence's benefits in energy efficiency. Therefore, the given effect of artificial intelligence on the INE is quite beneficial. With regard to the finding of a positive impact of ICT towards information energy, it is consistent with (**Wang *et al.***, 2023) who claim that more utilization of the ICT is connected with efficient energy resources. The given findings indicate that the pragmatic application of the several information and communication technologies' functions foster and drive the integration of clean energy sources. Therefore, it has been inferred that the positive connection between ICT and information energy is good in achieving sustainable outcomes specifically in the regional context of China.

The fourth explanatory variable under present research is entitled as the Environmental sustainability for which the impact on the information energy has been examined. The results in Table 6 for 50th percentile show that for the lower order quantile, the coefficient of ES is -0.488, which is highly significant at 1%, due to the lowest p-value. Similarly, the effect of the ES on the INE remains the same; however, for the 75th Quantile (Table 7), the coefficient was found to be -0.501. It means that from the .25th Quantile to 0.75th Quantile, there exists a significant and negative impact of the ES on the INE which is highly significant on statistical grounds. On similar grounds, the coefficient for the 90th Quantile (Table 8) was found as 0.401, which is also statistically significant at 1%. This negative and significant impact of the ES on INE implies that Environmental sustainability is causing a reduction in the generation of clean energy in China. Although there is an increasing trend in the Chinese economy toward efficient and technology-based energy systems, the portion of energy generated from fossil fuels is high. For example, almost 70% of China's energy comes mainly from fossil fuels. The energy from fossil fuels reflects a huge amount of investment in infrastructure related to traditional energy sources, which ultimately causes a reduction in energy generation at its potential capacity. Moreover, because of several economic benefits, there is a dominance of Environmental sustainability in China due to existing infrastructure, political influence, and higher resource extraction. However, contrary to our results, the research work conducted by **Rasheed *et al.*** (2024) reveals that Environmental sustainability are positively and significantly linked with modern energy for the sample of the 22 leading robotics and innovative countries.

The last variable for which the effect on information energy was examined was gross domestic product. The coefficient for the GDP towards INE under lower to higher order quantiles was 2.279, 2.876, and 2.159, showing a significance level of 1% with the p-value as less than 1%. The positive result shows that GDP has a potential role in promoting China's information energy. The stated research results are similar to what has been observed from the research contribution of the **Chu *et al.*** (2023) and **Nan *et al.*** (2023) regarding the influence of the beneficial influence of the GDP on the clean energy system. On the other hand, the effect of the GDP is negatively linked with environmental friendly energy as found by the **Xu and Wu** (2023) and **Radmehr *et al.*** (2021) from the context of the EU economies. These studies have explored the adverse relationship between economic growth and renewable and clean energy. The result of the current research aims to determine various factors on the relationship between economic growth and information energy.

Likewise, with the increasing level of economic growth in an economy like China, both the government and business organizations aim to invest more in several projects, including those that are renewable. With more prosperity, more funding is being available for manufacturing the wind farms, solar power plants, and hydropower stations, respectively. Meanwhile, higher economic growth often means more spending on research and development, leading to better and innovative energy technologies in the form of solar panels, and more efficient wind turbines. The given technological advancement would help improve energy sources while making them cheaper and easier to adopt for both the communize and business groups. Hence, it is a stronger competitor to traditional fossil fuels.

Additionally, with the growing trend of the economy, governments aim to collect more taxes and allocate financial resources to implement strategic policies that support efficient IT energy management. For business groups, a growing economy translates to higher profits and returns on investment, which encourages additional investments in IT infrastructure and energy efficiency projects. Many companies, particularly those in technology and manufacturing, are adopting advanced energy management practices to reduce costs, meet sustainability goals, and enhance their public image. In countries with high GDP, such as China, financial markets are also better developed, making it easier for businesses to secure funding for IT energy initiatives through options like green bonds or venture capital. Therefore, this research suggests that a higher GDP in the Chinese economy positively influences the promotion of effective IT energy management practices.

5. Conclusion and Policy Suggestions

The current research was carried out to examine the impact of the impact of artificial intelligence, information and communication technologies (ICTs), and technological innovations to examine the environmental sustainability, informational energy systems, and economic growth of China. Based upon the availability of the data for the main variables of interest, the study collected the annual observations during 2001-2020 for these variables while analyzing the influence of the stated explanatory variables on information energy by using the Methods of Moments Quantile Regression (MMQR) technique, which helped to divide the main outcome variable into several quantiles ranging from lower to higher orders. Meanwhile, before applying the MMQR, the study considered the descriptive statistics and tested them for the collinearity between the given variables through VIF and tolerance levels. Within the context of the MMQR estimator, the results show that the effect of artificial intelligence on the information energy is positive and significant from 0.25th to 0.90th quantiles, claiming that robotic industry is a good contributor for the sustainable energy solution when account for its production. Similarly, for information and communication technologies, the results are in favor of the condition that more infrastructure development in the form of ICT in China means a better, cleaner, and greener energy system. Moreover, the results favor the positive and productive impact of the increasing patents from the local residents which consequently boost the management of the energy in the information technology in China. However, the results show that Environmental sustainability impede the increasing share of the information energy in the entire energy system of China because of more dependence on the technological innovations. This research inferred that higher technological innovations are beneficial in leading to informational energy boost in China.

The results of the study provide several policy implications for environmental economists, policymakers, business groups, and even community members directly or indirectly linked to China's IT energy system. For example, the results support that artificial intelligence positively correlates with information energy in China. Therefore, the Chinese government must promote inter-regional collaboration to utilize artificial intelligence for information energy. Similarly, policymakers linked with technological innovations and energy systems need to exploit the potential of artificial intelligence to provide financial and non-financial assistance. This can be used by weather forecasting through different AI techniques, which can consequently benefit by checking the most optimal locations for defining the hydro, solar and wind power, hence maximizing the efficiency of the given energy sources. The second proposed policy implication is based on the notion that the Chinese government should continue to develop the infrastructure with a specific focus on information and communication technologies. Moreover, leveraging information and communication technologies for resource management, wind assessment, and circular economy practices may contribute to efficient and uninterrupted energy generation. However, one should not neglect the development of a robust cybersecurity infrastructure to safeguard the energy system from cyber threats.

The third key policy implication includes supporting technological innovations in the form of more recognition for the patent application residents. In this way, the support can consist of attention towards the institutional support for research and development, streamlining the patent application process and functional dimension, provision of more education and training for technological innovations, incentives for technological innovations, and higher collaboration with the different industries including the renewable and information energy projects. The fourth policy's implications aim to determine whether the Chinese government should reduce the share of energy from fossil fuels to diversify the energy production system with better contributions from renewable sources. Such diversification should also focus on increasing sustainable economic activities with low dependence on rental income from natural resources, minerals, etc. The research's fifth and last policy implication discusses the nexus between economic growth and IT energy management. To achieve sustainable economic progression, the Chinese government must establish competitive IT energy management zones. Suggested initiatives include creating dedicated research centers and financial units focused on energy-efficient technologies within the IT sector. Furthermore, the Chinese government and relevant authorities should implement strategic policies that encourage the adoption of energy-efficient practices across sectors, including transportation and manufacturing.

The study has limitations, which serve as a foundation for the upcoming studies. This study only takes data from the Chinese region while neglecting the other economies of the world that show a deep interest in informational energy and its management. This study neglects the role of the macroeconomic variables in their controlling influence over information energy. These factors might include inflation, urban population, digital infrastructure, financial development, green growth, research and development expenditure, etc. Besides, this research is time series while ignoring the panel data investigation. Future studies can address these limitations to develop better results and policies for the implications.

5.1. Acknowledgement

The Ministry of Education's Humanities and Social Sciences Research Planning Fund Project "Research on the Mechanism and Countermeasures of Digital Infrastructure and Intelligent Manufacturingnergistic Development" (22YJA790081).

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