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Toward energy security: The role of industrial intelligence and high-quality economic development

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ABSTRACT

Promoting energy security is an effective strategy for achieving sustainable development. However, rising energy demand has raised fears about energy insecurity (EIS), which poses a significant challenge for many nations. Industrial intelligence (IndInt) can help modernize the production process by promoting energy efficiency, green technology, and cost savings. Given the importance of industrial intelligence in promoting energy security, our study investigates the impact of industrial intelligence and high-quality economic development (HQED) on EIS in China, using data from Chinese provinces from 2007 to 2017. For empirical investigation, a fixed-effects model with Driscoll-Kraay standard errors (FE-DKSEs) is employed. For the sake of robustness, feasible generalized least squares (FGLS) and panel-corrected standard errors (PCSEs) are also applied. Based on the study results, the relationship between industrial intelligence and EIS is non-linear and statistically significant. HQED and EIS are negatively associated, showing that HQED significantly contributes to mitigating EIS. Moreover, the moderating role of HQED in EIS reduction through industrial intelligence is demonstrated. Further, our study findings are robust to the inclusion of various controls. Urbanization and exports increase EIS. Industrial intelligence is helpful in achieving energy security in China. The government should devise policies that promote industrial intelligence to achieve energy security, as energy security is a prerequisite for sustainable development.

Contribution/Originality: To study the impact of IndInt on EIS in China, comprehensive metrics of IndInt and EIS are employed. The EIS is constructed using total energy supply and demand, which are aggregations of the main energy sources produced and consumed. The moderating role of HQED and IndInd on EIS is explored.

1. INTRODUCTION

With the rapid industrialization and economic development of China, the country is now the world's second biggest economy (Zhao, Gao, & Sun, 2023). However, this rapid development has resulted in an energy shortage and raised concerns about energy security (Lee, Yuan, & Wang, 2022). China accounts for about 75% of the net increase in the world's energy consumption (henceforth, EC) and has emerged as the major global driving force (Liu, Qian, Yang, & Yang, 2022). However, the huge EC by China can lead to energy depletion, limiting the country's sustainable development (Zhu & Lin, 2022). To achieve sustainable development, the government of China has prioritized energy conservation (Zhu & Lin, 2022). The China Energy Work Conference 2021 has been dedicated to the firm application of the "twofold control" system, which includes total EC and intensity, and total EC restricted to five billion tons of standard coal, at an average yearly growth rate of below 3% (Liu et al., 2022). The Chinese government in its 12th Five-Year Plan (2011-2015), unwaveringly stimulated the energy revolution, causing remarkable changes in energy production and utilization, and increasing the ability to guarantee energy security (Li, Ma, Qu, & Wang, 2023). Moreover, the 13th Five-Year Plan (2016-2020) pledged to decrease energy intensity by about 15% compared to its baseline in 2015 (Liu, Yang, Fujii, & Liu, 2021). Therefore, it is necessary to explore the major factors influencing EIS reduction and make valuable recommendations that are useful in formulating effective EIS reduction strategies (Huang & Chen, 2020). With the fast global technological revolution, industrial intelligence has become vital in promoting manufacturing (Liu et al., 2022). Specifically, by integrating modern technologies like AI, big data analytics, cloud computing, and the Internet of Things into industrial production, businesses gain control over intelligent production, operational decision-making, and resource deployment (Tao, Wang, & Zhai, 2023). Enormous datasets and intelligent infrastructures are the basic inputs for industrial intelligence, while the industrial internet offers intelligent connective platforms (Siqi Chen et al., 2023). Thus, industrial intelligence is a broader concept as it reflects a wide spectrum of technological developments and numerous innovations across industries (Wang, Chen, Dong, & Cheng, 2024). More precisely, industrial intelligence is the use of AI technology in industrial production, which is estimated to be the newest technique for saving energy, mitigating environmental concerns, and promoting green transformation production modes (Tang & Chi, 2022). The "Made in China 2025" plan demonstrates the intentions of China to accelerate industrial intelligence; the goal of transforming traditional manufacturing methods into intelligent manufacturing is the primary strategy for reducing emissions and creating a green and low carbon industry (Yin & Zeng, 2023). Through better connectivity of the information systems and production, industrial intelligence permits intelligent supply chains, technological gains, lower emissions, and reduced environmental impact (Wang, Lee, & Li, 2022).

In existing studies, singular indexes (i.e., robotics, computerized devices, artificial intelligence patents) have been commonly used to measure IndInt (Acemoglu & Restrepo, 2020; Damioli, Van Roy, & Vertesy, 2021; Li et al., 2023; Liu et al., 2022; Liu et al., 2021; Xian, 2023; Yin & Zeng, 2023; Zhang, Liu, & Zhu, 2022). However, these proxies do not fully reflect industry intelligence. Moreover, statistical indexes have been developed to conduct comprehensive examinations of IndInt. Wang et al. (2022) constructed an IndInt composite index; however, the study only considered the output and technology dimensions, instead of a complete cycle management coverage. Based on the IndInt concept of full-cycle management from initiation to implementation and performance, and following Wang et al. (2024), our study uses a comprehensive index to assess the IndInt level in China. This index covers three aspects: intelligent inputs, intelligent production capabilities, and intelligent output. Our study uses this index to determine whether IndInt contributes to EIS reduction in China.

HQED plays a dominant role in achieving energy security and sustainability (Li, Lin, Wang, & Wang, 2022). However, the unsustainable and extensive growth of an economy has greatly hindered its sustainable economic development and intensified EIS. Therefore, countries are moving from traditional high-speed economic growth to HQED to promote energy security (Skawińska & Zalewski, 2023). Cooperation among several parties, assistance from country policy, and efficient utilization of resources with the help of public efforts, modern skills, expertise, knowledge, patented technologies, and innovations are all indispensable for economic development. These activities work effectively together to produce HQED, which helps to reduce EIS (Wang, 2022). Additionally, the 14th Five-Year Plan summarized the intentions of China regarding HQED with a focus on upgrading reforms related to supply-side restructuring as the major driving forces of energy security (Zhou, Li, Lin, & Cheng, 2022). This study focuses on China because of its prioritization of policies related to EIS reduction. Furthermore, China is currently transitioning from high-speed EG to HQED; a development that leads to declines in EIS (ADB, 2021). Therefore, China is a unique case study that provides an excellent opportunity to explore the issue of EIS.

This study contributes to existing research as follows: firstly, it investigates the impact of IndInt and HQED on EIS using Chinese province-level data from 2007-2017. The study by Liu et al. (2022) for China focused only on energy efficiency, energy intensity, energy and resource efficiency, and overlooked EIS, which is considered a key energy indicator. Second, to measure EIS we subtract aggregate supply from aggregate demand. Similar to Ul-Haq, Mushtaq, Visas, Hye, and Rehan (2023) our study constructs an inclusive metric of EIS using the total energy supply (production) and total energy demand (consumption), which are the aggregation of the main energy sources (i.e., coal, diesel, coke, electricity, crude oil, kerosene, gasoline, natural gas, fuel oil) produced and consumed. Before aggregation and to avoid mathematical errors, the various units from the different sources are converted to the same measuring unit- quadrillion British thermal units (QBTU). This measure is better than previously used energy insecurity indicators. Third, similar to Wang et al. (2024) this study uses an IndInt index incorporating intelligent inputs, intelligent production capabilities, and intelligent output. Fourth, we investigate the moderating role of HQED and IndInt (HQED*IndInt) in EIS reduction.

The rest of the paper is structured as follows: Section 2 presents the literature review on the association between IndInt, HQED, and EIS; Section 3 presents the methodology; Section 4 details the study findings; and Section 5 concludes the study and provides policy implications.

2. LITERATURE REVIEW

World energy market shocks have redirected researchers' focus towards energy security. While EIS is an important issue that must be addressed immediately, there is a need to assess the precise picture of EIS using accurate measures. In existing studies, the composite index and single indicator are the most commonly utilized proxies for quantifying EIS. However, there are no commonly accepted criteria for quantitatively measuring the EIS. Moreover, existing research on energy security has focused on two areas. The first strand of research focuses on defining the concept of EIS, constructing EIS indicators, and conducting a comprehensive appraisal. For example, Chester (2010) measured EIS using the energy demand index, energy supply index, and oil vulnerability index. Le and Nguyen (2019) developed a five-dimensional energy security metric: energy accessibility, availability, affordability, acceptability, and developability. Moreover, energy availability, energy intensity, and clean energy ratio are used as indicators of EIS (Rakpho, Yamaka, Puttachai, & Maneejuk, 2021). The second stream of research focuses on factors influencing EIS, such as economic, financial, environmental, sociopolitical, and technological factors. Godil, Sharif, Ali, Ozturk, and Usman (2021) demonstrated that energy use in India is affected by financial development (FD), institutional quality, R&D investment, and globalization. Duan and Hu (2013) showed that technological innovation and industrial structuring significantly promote energy efficiency. Shahbaz and Lean (2012) and Ma and Fu (2020) found that the relationship between financial development and EC is negative.

2.1. Industrial Intelligence and Energy Insecurity

Some studies have explored the environmental impacts of IndInt, but the majority of existing studies on the topic have focused on the labor market and its economic consequences (Acemoglu & Restrepo, 2020; Ballestar, Díaz-Chao, Sainz, & Torrent-Sellens, 2020; Du & Lin, 2022). Many studies have analyzed how economic growth, FDI, and others, as well as ICT, influence EIS, but their findings have been mixed (Suisui Chen, Zhang, & Wang, 2022; Deichmann, Reuter, Vollmer, & Zhang, 2019; Hao et al., 2022). However, it is undeniable that studies on the nexus between IndInt and EIS are limited, despite the vital role played by industrial intelligence in promoting energy security. In the energy-economics literature, studies have highlighted some contributing factors, such as income per capita (Agovino, Bartoletto, & Garofalo, 2019; Jimenez & Mercado, 2014), openness to trade (Pan, Uddin, Saima, Jiao, & Han, 2019; Rafiq, Salim, & Nielsen, 2016), technological innovation (Lee & Wang, 2022; Wurlod & Noailly, 2018), and geopolitical risks (Lee, Yuan, He, & Xiao, 2024). AI is anticipated to be a basic technology that can promote more innovations (Liu, Chang, Forrest, & Yang, 2020). AI is used by enterprises to achieve technological progress, which tends to further boost TI (technological innovations), thus creating a new virtuous circle (Vocke, Constantinescu, & Popescu, 2019). AI influences the EIS in different ways. Firstly, it accelerates knowledge spillover and promotes enterprises' technological progress in energy saving and cleaner production, which enhances energy efficiency (Sun, Edziah, Kporsu, Sarkodie, & Taghizadeh-Hesary, 2021). The greater the capability of an enterprise to absorb and learn, the greater its ability to innovate (Vlačić, Dabić, Daim, & Vlajčić, 2019). Through computer vision technology and deep learning, AI can filter out a large amount of useful information to provide advanced knowledge and more efficient modern computing solutions, thereby hastening the knowledge reorganization process (Catania, 2021). The hastening of knowledge reorganization can stimulate the regeneration of information and knowledge (Leary, 2013). Similarly, AI breaks down knowledge diffusion frontiers facing enterprises and can accelerate information sharing and knowledge spillover, which boosts technological innovation (Goldfarb & Trefler, 2018). This, in turn, stimulates industrial modernism, resulting in equipment and energy use optimization decisions that promote energy efficiency (Vocke et al., 2019).

Secondly, AI stimulates technological progress and promotes energy efficiency by enhancing investment in R&D and talent. AI development leads to more intelligent devices like industrial robots and produces the labor substitution effect (Acemoglu & Restrepo, 2018). The high-skilled labor shortage caused by this complementary labor substitution will further encourage manufacturing enterprises to increase investment in R&D (Ma, Gao, Li, & Zhang, 2022), which further stimulates technological progress (Jiang, Fu, & Li, 2020). Moreover, with the increase in industrial robot use, companies have enhanced their manufacturing skills and production processes. Thus, the production process is optimized with technological progress, thereby promoting energy efficiency (Ahmad & Zhang, 2021), which reduces EIS. Based on the literature, our study states the hypothesis (H1):

H_1: IndInt can reduce energy insecurity.

2.2. HQED and Energy Insecurity

China's economy is currently transitioning from rapid economic growth to High-Quality Economic Development (HQED), and it is at a critical point in altering its development mode, growth drivers, and economic structure. Specifically, HQED has five dimensions: innovation, openness, green, coordination, and sharing. It is an innovative concept that symbolizes the transformation and development of the growth of an economy from quantity to quality. Several existing studies have identified the influencing factors of HQED. Wang, Dong, and Taghizadeh-Hesary (2024) explored the role of green finance in promoting HQED in China during the period 2007-2019. The study found that green finance has a positive and statistically significant effect on HQED. Gao, Li, and Hao (2024) examined the relationship between governance ability, resource dependence, and HQED in China. The results showed that resource dependence has an inhibitory effect on HQED and that governance ability exacerbates the influence of resource dependence on HQED. The studies of Gu, Wang, Hua, and Liu (2021); Ding, Liu, Zheng, and Li (2021) and Tsaurai and Ndou (2019) concluded that institutional and technological innovation play an important role in boosting HQED. Other studies have examined the effect of the digital economy (Yang, Deng, Wang, & Xiang, 2022; W. Zhang, Zhao, Wan, & Yao, 2021) industrial structure (Wang, Wang, & He, 2022; Zeng, Shu, & Ye, 2022) platform economy (Yang et al., 2022) foreign direct investment (FDI) (Huang, Binqing, & Yalin, 2020; Jahanger, 2021) environmental regulation (Liu, Liu, Wang, Zhao, & An, 2021) carbon emissions (Zhang, Zhang, & Bai, 2021) education equity (Arceo, Hanna, & Oliva, 2016; Gu et al., 2021) and many others. Badinger (2010) investigated the causal effect between economic growth and output volatility. According to Zhao et al. (2023) remarkable development in energy efficiency has supported China's transition from rapid to efficient growth. Energy is a critical input in production, and HQED is reflected in energy efficiency development. Ren and Zhang (2023) investigated the relationship between HQED, clean energy consumption, and the digital economy in China for the period 2011-2020. The study found that the digital economy is vital in promoting HQED. Thus, we conclude that there is no study particularly in the case of China, about the impact of HQED on Economic Innovation System (EIS). Based on the above literature, the second hypothesis is as follows:

H_2: HQED can reduce energy insecurity.

2.3. Urbanization and Energy Insecurity

The presently unprecedented urbanization of China has caused more EC. In this context, Li, Li, and Strielkowski (2019) explored the intrinsic link among energy security, urbanization, and industrialization in China using provincial data from 2006-2015. The study revealed that industrialization and urbanization promote energy efficiency. Fikir and Abebe (2020) analyzed the effect of urbanization, income per capita, and industrialization on energy security. The study, using the Africa dataset for the period 2000-2019, found that income per capita, industrialization, and urbanization promote energy security. Sadorsky (2013) found a mixed association between urbanization and energy security. Chen and Zhou (2021) examined the relationship between energy intensity and urbanization utilizing panel data from 71 countries spanning 2000-2014, and found that more urbanization causes more energy intensity. Elliott, Sun, and Zhu (2017) demonstrated the direct and indirect impacts of urbanization on energy intensity in China during 1995-2012. The empirical estimates showed a positive influence of urbanization through direct effects, while negative through indirect effects. Bilgili, Koçak, Bulut, and Kuloğlu (2017) explored the link between urbanization and energy intensity in 10 Asian economies using data from 1990-2014. The study found that the association between urbanization and energy intensity is negative. Based on the above literature, the third hypothesis of this study is as follows:

H_3: Urbanization increases energy insecurity.

2.4. Exports and Energy Insecurity

Using survey data of Chinese firms, Freitas, Jacob, Wang, and Li (2023) investigated the nexus between exports and energy use and found a positive relationship between exports and energy use. Thus, as international trade expands, the world experiences the issue of energy shortages. The study by He and Huang (2023) analyzed the impact of export liberalization on energy efficiency. The study recommends that export liberalization promotes firms' productivity and innovation ability, which enhances energy efficiency. Employing plant-level data from manufacturing between 2008 and 2015, Goldar and Goldar (2023) assessed the link between export intensity and energy intensity in India. The findings reveal that export intensity has a negative statistically significant impact on energy intensity. Zhao and Hong (2008) examined the impact of international trade on EC between 1997 and 2000 and demonstrated that net exports had a significant impact on the volume of energy consumed. Based on this literature, the fourth hypothesis of this paper is as follows:

H_4: Export can stimulate energy insecurity.

In conclusion, despite extensive empirical investigations in the field of energy economics, there are still some limitations. First, no study has used the comprehensive measure (i.e., AD-AS) of EIS, which is important for a country's sustainable development. Second, existing studies use single indices rather than an IndInt index that includes intelligent inputs, intelligent production capabilities, and intelligent output. Third, no study has used the HQED index, which incorporates innovation, green development, economic coordination, openness, and achievement sharing. A brief summary is presented in Table 1.

Table 1. Literature review.

Study	Country	Sample period	Method	Model	Outcome
Ul-Haq, Visas, Hye, Rehan, and Khanum (2024)	Provincial panel China	2011-2017	FE-DKSE	EIS = f (EG, HQED)	EG increase EIS HQED reduce EIS
Li et al. (2023)	Firm-level China data	2005-2014	FE	Energy & resource efficiency = f (AI)	Improve energy & resource efficiency
Xian (2023)	China 30 provinces	2011-2019	FE	Energy efficiency = f (Intelligence)	Promote energy efficiency
Rong, Wang, and Zhang (2023)	30 China provinces industrial sector	2015-2018	STIRPAT & spatial moderation model	TFP = f (IndInt)	Increase in total factor productivity
Yin and Zeng (2023)	30 China provinces	2006-2020	Threshold	Energy intensity = f (IndInt)	Reduce energy intensity
Wang et al. (2022)	38 countries, 17 manufacturing sectors	2000-2014	GMM	Energy intensity = f (IndInt)	Improve energy intensity
Lee and Wang (2022)	30 China provinces	2000-2018	FE, RE, IV	Energy security f (TI, FD)	Improve energy security
Liu et al. (2022)	China Guangdong Province	2013-2015 (110,000 manufacturing enterprises)	Two-way FE	Energy efficiency = f (AI)	Boost energy efficiency

Note: FE denotes fixed effect, IndInt denotes industrial intelligence, AI denotes artificial intelligence, TI denotes technological innovation, FD denotes financial development, and TFP denotes Total factor productivity.

3. THEORETICAL FRAMEWORK

IndInt contributes significantly to the promotion of energy security through a variety of channels, including the first, scale effect; second, technological innovation effect; and third, industrial upgrading effect. First, IndInt, through the scale effect, allows for productivity gains and contributes to increased aggregate output, resulting in improved energy efficiency and lower per unit energy costs; a practice that aids in EIS reduction (Kunkel & Matthess, 2020). Second, the technological innovation effect achieved by using robots or digital technologies decreases the cost of production, allowing industries to invest more in innovation-related actions, which are beneficial to productivity growth, the use of renewable energy, and eco-friendly TI. These outcomes, in turn, lead to less EC and reduce EIS (Wang et al., 2022). Third, the industrial upgrading effect through the use of IndInt can stimulate the green and intelligent transformation of traditional sectors and boost efficiency in production (Tang & Chi, 2022). Consequently, traditional industries with high- EC are gradually upgraded and transformed into less polluting and less- EC industries, resulting in EIS reduction (Huang, He, & Lin, 2022). Fourth, green employment and the use of IndInt may increase unemployment as human labor is increasingly substituted with machines (Acemoglu & Restrepo, 2020).

The study by Chen, Cheng, and Lee (2022) postulates that labor force substitution with machines encourages the mobility of labor and reduces the workforce in relatively polluted industries, thus enhancing relatively eco-friendly agriculture and service sectors. The increased use of IndInt has also generated many "green jobs," like R&D technology positions, which have also resulted in a reduction in EIS. Additionally, enterprises can proficiently design product recycling as well as waste treatment with the support of IndInt, which will efficiently decrease EC and waste of resources. HQED is a contributing factor in energy security. HQED applies efficient technologies and enhances EC efficiency, which promotes the EC structure and reduces EIS (Du, Zhang, & Li, 2020).

4. DATA

This study uses province-level data from China from 2007 to 2017 to explore the impact of IndInt and HQED on EIS. The panel model is used in which EIS is the regressand variable. The data for the EIS variable is taken from CNBS (2022). The regressors are IndInt, HQED, and IndInt*HQED for the moderating effect. The data for IndInt and HQED are taken from Wang et al. (2024) and Du et al. (2020), respectively. The data for urbanization and exports, used as control variables, are collected from CNBS (2022). The definitions of the variables and descriptive statistics are in Table 2 and Table 3, respectively.

Table 2. Variable definition.

Variables	Code	Definition	Sources
Energy insecurity	EIS	Aggregate demand minus aggregate supply (i.e., AD-AS).	CNBS (2022)
Industrial intelligence	IndInt	IndInt index pertaining to intelligent input, intelligent production capacity, and intelligent output.	Wang et al. (2024)
High-quality economic development	HQED	HQED index containing innovation driven, green development, economic coordination, opening up, achievement sharing.	Du et al. (2020)
Urbanization	Urban	Share of urban population.	CNBS (2022)
Exports	LX	Log of exports.	CNBS (2022)

Table 3. Descriptive statistics.

Variables	Obs.	Average	S.D	Minimum	Maximum
EIS	330	2.708	2.075	-0.617	12.810
IndInt	330	0.267	0.343	0.025	2.644
HQED	330	0.274	0.166	0.058	0.979
Urban	330	0.542	0.136	0.273	0.904
Export	330	18.63	1.611	14.358	22.161

4.1. Measurement of Energy Insecurity

Following Ul-Haq et al. (2023), EIS is computed by subtracting aggregate energy supply from the aggregate energy demand. Our study uses an inclusive metric that covers both sides (i.e., demand and supply) of energy, which is the accumulation of the core energy sources (i.e., fuel oil, kerosene, coal, electricity, crude oil, natural gas, coke, diesel, and gasoline) produced and consumed. To avoid mathematical errors, the energy units were converted to a unified measuring unit (quadrillion British thermal units (QBTU)) before aggregation. As far as studies on EIS are concerned, this research is the first, at least in China, to utilize both the supply and demand from all energy sources as a comprehensive measure of the EIS.

4.2. Measurement of Industrial Intelligence Index

This study develops the IndInt index contingent on the Chinese government document (MIIT, 2021) and influential literature (Wang et al., 2022). This index incorporates three measurements: intelligent input, intelligent production capacity, and intelligent output. The index is constructed using the entropy weight method. The study data for IndInt are taken from Wang et al. (2024). High-tech.

4.2.1. Intelligent Input

Infrastructure and capital required for IndInt are reflected in the intelligent input. It contains intelligent work and internet infrastructure, intelligent research and development, sophisticated inputs, and intelligent equipment inputs.

4.2.2. Intelligent Production Capacity

The capacity of intelligent production reflects industrial intelligence to engage in manufacturing and production. To compute the intelligent production capacity, and following Wang et al. (2022), our research uses big data processing, intelligent manufacturing equipment, intelligent production lines, network operation and maintenance, and intelligent supply. Each secondary indicator is determined through the number of enterprises included in the supply chain and intelligent production processing lines. Furthermore, the collection of keywords depends on authoritative literature like Kinkel, Baumgartner, and Cherubini (2022) and Frank, Dalenogare, and Ayala (2019), and government publications.

4.2.3. Intelligent Output

The firm's IndInt technological and economic output is reflected in the intelligent output. It includes technology output, general and electronic equipment output, total factor productivity, and product innovation income. Table 4 presents the full index detail.

Table 4. Industrial intelligence index.

	Primary indicators	Secondary indicators	Attributes
Industrial intelligence	Intelligent input	Inputs of intelligent equipment	Imported industrial robots' total value
		R&D high-tech inputs	Length of fiber-optic lines
		R&D intelligent inputs	Internal expenditure on R&D funding in manufacturing enterprises
		Intelligent network formation	Fiber-optic lines length
		Internet infrastructure formation	No. of internet broadband ports accessed
	Intelligent production capacity	Supply chain of intelligent	No. of enterprises involved in intelligent supply chain operations

	Primary indicators	Secondary indicators	Attributes
		Production line of intelligent	No. of enterprises involved intelligent production line operations
		Manufacturing intelligent equipment	No. of enterprises involved in the intelligent equipment manufacturing
		Network maintenance & operation	No. of enterprises involved in the network maintenance & operation
		Large data processing	No. of enterprises involved in the processing of large data
	Intelligent output	Total factor productivity	Total factors production rate
		Output from general equipment	Manufacturing general equipment operating income
		Output from electronic equipment income from innovative product	Communication computer, equipment & other electronic equipment manufacturing operating income
		Technology output	Operating income of new product
			No. of effective inventions

Source: Wang et al. (2024).

4.3. Measurement of High-Quality Economic Development

Following Du et al. (2020) and Ul-Haq et al. (2024), this study, based on data availability, measures the HQED using green development, economic coordination, achievement sharing, opening up, and innovation-driven aspects, as disclosed in the study by Du et al. (2020). This index is fully embodied in five new development concepts: coordination, innovation, green, sharing, and openness. The HQED data is obtained from the study of Du et al. (2020). The HQED index is superior to previously used single-variable measures such as total factor productivity (Jahanger, 2021). The single-variable measure is unable to accurately capture the true connotation of HQED. Moreover, a wide-ranging multi-index assessment method is also utilized in existing research, which pertains to economic, societal, and ecological indicators (Gu et al., 2021).

4.4. Regression Model

This research aims to explore the potential of IndInt and HQED in EIS reduction. Therefore, the model is stated as follows:

$$EIS_{it} = \beta_0 + \beta_1 IndInt_{it} + \beta_2 IndInt^2{}_{it} + \beta_3 HQED_{it} + \beta_4 IndInt * HQED_{it} + \beta_5 Z_{it} + \varepsilon_{it} \quad (1)$$

Where EIS represents energy insecurity, IndInt presents the industrial intelligence level of Chinese province i in year t. $IndInt^2$ is the squared term of the IndInt. The vector Z represents the set of control variables containing urbanization and exports, and ε_{it} denotes the model error term. Our study extends the empirical model by including IndInt as a significant predictor of the EIS. This research expects that β_1 will be positive, revealing that IndInt plays a positive role in reducing EIS. Meanwhile, we expect β_2 to be negative, showing that $IndInt^2$ has a negative impact on EIS. Thus, our study anticipates a nonlinear relationship between IndInt and EIS. Furthermore, we expect β_3 to be positive, demonstrating that HQED can reduce EIS. We expect that β_4 to be positive, indicating that the interactive term IndInt*HQED plays a positive role in EIS reduction. Regarding urbanization and exports, our study predicts that both will increase EIS.

4.5. Estimation Technique

The FE-DKSE method is used to estimate the impact of IndInt and HQED on EIS. Cross-sectional dependence (CSD) is a major problem, and its presence in the dataset produces misleading results. Therefore, to produce precise and accurate estimates, issues of CSD must be addressed. The FE-DKSE approach essentially handles CSD issues.

Similarly, it considers the error structure to be heteroscedastic and autocorrelated up to a certain lag and related across entities.

The nonparametric process in the DKSE estimator is more consistent without imposing constraints on the number of panels restraining behavior, and it becomes more reliable as the time length increases; however, the estimator is based on greater T asymptotic. Furthermore, the Driscoll-Kraay covariance estimator can account for missing data and work effectively with balanced and unbalanced panel data. DKSE for the pooled estimation is presented as follows:

$$y_{i,t} = x_{it}'\beta + \varepsilon_{i,t}, i = 1, \dots, N;\ t = 1, \dots, T \qquad (2)$$

Where, $y_{i,t}$ is regressand variable (i.e., EIS), $x_{i,t}$ specifies the regressor variables (IndInt, IndInt², HQED, IndInt*HQED, Urb, and exports) with vector (K + 1) × 1, whose initial element is the 1, and unknown coefficients shown by β with vector (K + 1) × 1, and cross-sectional units dented by I at time t. Afterward layering the observations, the formulation is as follows:

$$y = \left[y_{1,t_{1,1}}, \dots\dots, y_{1,T_1} \quad y_{2,t_{2,1}}, \dots\dots, y_{N,T_N}\right]' \qquad (3)$$

and

$$X = \left[x_{1,t_{1,1}}, \dots\dots, x_{1,T_1} \quad x_{2,t_{2,1}}, \dots\dots, x_{N,T_N}\right]' \qquad (4)$$

Consider that the scalar error term ($\varepsilon_i s$) are unconnected to $x_{i,t}$ for all s, t (robust exogeneity). $\varepsilon_{i,t}$ can though show CSD, autocorrelation, and heteroscedasticity. On the basis of the specified assumption, taking the OLS regression β can be consistently estimated, as in Hoechle (2007):

$$\widehat{\beta} = (X'X)^{-1}X'y \qquad (5)$$

The coefficient of DKSE estimates are represented by the "square roots of the diagonal elements of the asymptotic covariance matrix" (Driscoll & Kraay, 1998):

$$V(\hat{\beta}) = (X'X)^{-1}\hat{S}_T(X'X)^{-1} \qquad (6)$$

5. RESULTS AND DISCUSSION

Table 5 presents the modified Wald, Wooldridge, and Pesaran test results. The outcome of the modified Wald test for heteroscedasticity indicates that heteroscedasticity exists in the data. The study rejects the null hypothesis and accepts the alternative at the 1% significance level. Furthermore, the results of Friedman's test and the Pesaran CD test for cross-sectional dependence (CSD) confirm its existence at the 1% level.

Table 5. Diagnostics tests.

Modified Wald test	**Friedman's test**
18223.55***	98.024***
Pesaran test of cross sectional independence	
15.823***	
Pesaran, Schuermann, and Weiner (2004) test	
EIS	35.19***
IndInt	58.93***
HQED	31.66***
Urban	52.95***
LX	46.72***

Note: Asterisk shows significance level *** denotes 1%.

To detect multicollinearity, the VIF test is used, and findings are provided in Table 6. If there are no VIF values greater than the rule of thumb of 10, it indicates that there is no multicollinearity.

Table 6. VIF test.

Variable	VIF	1/VIF
Urban	4.43	0.226
HQED	3.69	0.271
LX	2.59	0.386
IndInt	1.97	0.508
Mean	3.17	

The FE-DKSE estimates are presented in Table 7. Column 1 reveals that the influence of IndInt on EIS is positive and statistically significant, demonstrating the increasing trend of EIS. The negative coefficient of $IndInt^2$, which is also significant at the 1% level, demonstrates that it significantly lessens EIS. Thus, IndInt and EIS are linked. The empirical estimates indicate the non-linear association between IndInt and EIS, suggesting that initially, IndInt leads to an increase and then a decrease in EIS. Every model shows significant Wald statistics. The estimate of the influence of HQED on EIS given in column 2 demonstrates the inverse relationship between HQED and EIS. Thus, HQED contributes positively to reducing EIS. Moreover, HQED leads to the use of energy-efficient production methods, lower EC, and greater energy savings, which promotes energy security. This finding recommends that to promote energy security objectives, attention must be directed toward HQED. HQED has the ability to move sectors from old to advanced production methods, which can contribute to lower EC and lesser EIS. This study's findings are in line with Sun et al. (2021) and Dogan, Chishti, Alavijeh, and Tzeremes (2022). Further, our study investigates the moderating variable effect (HQED*IndInt) in reducing EIS. The HQED*IndInt coefficient indicates a negative sign, suggesting that IndInt also indirectly reduces EIS through HQED. Furthermore, using the FGLS and PCSE methods, our study found similar results as seen in columns 3-4 & 5-6 respectively.

Table 7. Nexus among IndInt, HQED, and EIS in China.

Variables	FE-DKSE	FE-DKSE	FGLS	FGLS	PCSE	PCSE
IndInt	7.449*** (0.524)	10.73*** (1.011)	6.885*** (0.340)	9.354*** (0.763)	7.449*** (0.633)	10.73*** (1.226)
$IndInt^2$	-2.351*** (0.346)	-2.391*** (0.405)	-2.037*** (0.211)	-1.911*** (0.273)	-2.351*** (0.320)	-2.391*** (0.351)
HQED		-1.418** (0.612)		-0.991* (0.510)		-1.418* (0.754)
IndInt*HQED		-8.733*** (2.489)		-6.672*** (2.122)		-8.733*** (3.074)
Constant	1.165*** (0.102)	1.420*** (0.226)	1.031*** (0.0622)	1.219*** (0.135)	1.165*** (0.150)	1.420*** (0.272)
Wald/F-Stat.	1008.95	781.37	840.91	631.04	242.13	358.34
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	330	330	330	330	330	330

Note: Asterisk show significance level *** denote 1%, ** denote 5%, and * denote 10%.

The main study model is expanded to include exports and urbanization, which are generally used in the literature as core factors influencing EIS. The robustness checks are done to test how stable the core findings were. Table 8 shows the robustness check results. After incorporating Urb and exports, the study results remain significantly robust. The FE-DKSE (columns 1-3), FGLS (column 4), and PCSE (column 5) methods reveal the nonlinear relationship between IndInt and EIS, and a negative relationship between HQED and EIS. Moreover, the interactive term (IndInt*HQED) also shows a reduction in EIS. However, empirical models demonstrate that our main findings remain the same and significant. The link between urbanization and EIS is significantly positive, showing that rising urbanization increases EIS. The rapid increase in urbanization causes more EC and results in EIS. This finding is in line with Li and Lin (2015) who found that urbanization increases EC for lower-middle-income economies, but not for upper-middle-income economies, and in contrast with Fikir and Abebe (2020) and Li et al. (2019) who found that urbanization significantly promotes energy efficiency. Regarding exports, the findings show that exports are positively related to EIS, implying that EIS increases with more exports. The implication of this finding is that as a country's exports increase, it requires more energy to produce more, resulting in rising EIS. These results are in line with Freitas et al. (2023) and oppose He and Huang (2023).

Table 8. Nexus among IndInt, HQED, and EIS in China (Robustness checks).

Variables	DKSE	DKSE	DKSE	FGLS	PCSE
IndInt	10.73*** (1.011)	10.55*** (1.046)	10.54*** (0.548)	10.54*** (1.396)	10.54*** (1.396)
$IndInt^2$	-2.391*** (0.405)	-2.294*** (0.425)	-2.292*** (0.350)	-2.292*** (0.408)	-2.292*** (0.419)
HQED	-1.418** (0.612)	-2.409** (0.777)	-2.410*** (0.694)	-2.410** (1.178)	-2.410** (1.112)
IndInt*HQED	-8.733*** (2.489)	-9.062*** (2.634)	-9.060*** (2.474)	-9.060** (3.672)	-9.060*** (3.228)
Urban		1.613** (0.600)	1.611* (0.784)	1.611 (1.289)	1.611 (1.409)
LX			0.000755 (0.0952)	0.000755 (0.0973)	0.000755 (0.0924)
Constant	1.420*** (0.226)	0.875*** (0.203)	0.864 (1.564)	0.864 (1.570)	0.864 (1.489)
Wald/F-Stat.	781.37	717.90	765.45	293.63	336.75
P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	330	330	330	330	330

Note: Asterisk show significance level *** denote 1%, ** denote 5%, and * denote 10%.

6. CONCLUSION

EIS has emerged as the most pressing issue confronting the country's sustainable development and policymakers. Besides, HQED can generate a larger quantity of products while reducing EC. Considering the significance of IndInt and HQED, this paper explored the influence of IndInt and HQED on EIS in China, using data from Chinese provinces from 2007 to 2017. The FE-DKSE, FGLS, and PCSE methods show a non-linear relationship between IndInt and EIS. The liaison between HQED and EIS is negative, demonstrating that it reduces EIS. Further, the interactive term (IndInt*HQED) reveals that IndInt significantly reduces EIS through HQED. The study findings are robust after the inclusion of urbanization and exports as controls.

Based on the study's findings, it is critical to dynamically implement effective policies to encourage the IndInt to reduce EIS. As a result, IndInt development support measures should be implemented to maximize its significant influence in reducing EIS. For instance, subsidies and tactical support could be designed for the intelligence control system, general intelligence types of equipment, and manufacturing instruments to increase enterprises' intelligent production capacity. Furthermore, the government should endorse strategies that stimulate HQED and contribute to energy sustainability. Our study findings make a significant contribution and recommend that the government prioritize the HQED to hasten the process of improving energy security, which is important in achieving SDG-7. Furthermore, with the continued elevation of HQED's innovation abilities, it is critical to improve technology, generate new momentum, transform technology, achieve scientific breakthroughs, and innovate institutions. The potential limitation of this study is that we used the 2007-2017 sample period due to data scarcity. This study adds to the existing body of literature on energy security by taking into account other major factors influencing energy security, including social, environmental, and economic factors.

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