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Research on the impact of digital economy development on mineral resource utilization efficiency

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The international geopolitical crisis and the rigid management system increase the risk of a mineral crisis in China, but the development of the digital economy provides a possibility for the efficient utilization of mineral resources. Based on the panel data of 30 provinces (autonomous regions and municipalities) from 2011 to 2022, this research measures the level of China's digital economy development and the utilization efficiency of mineral resources, and examines the transmission path of the digital economy development on the utilization efficiency of mineral resources by using the mediation effect model. The results show that (1) the development of the digital economy can significantly improve the utilization efficiency of mineral resources, and this conclusion is still valid after the instrumental variables method and other robustness tests. For every unit of progress in the development of the digital economy, mineral resource efficiency improves by 0.226. (2) The upgrading of industrial structure and technological progress play a mediating role in the digital economy and the improvement of mineral resource utilization efficiency. (3) The digital economy has a significant heterogeneous effect on the utilization efficiency of mineral resources in China's eastern, central, and western regions, with the most prominent positive effect in the central and western regions. The positive effect is most prominent in the Midwest at 0.180, and is not significant in the East.

KEYWORDS

digital economy, mineral resource efficiency, super-efficiency SBM-DEA, system GMM, mediation effects

1 Introduction

Mineral resources constitute a critical material foundation for the survival and advancement of human society, and their responsible exploitation and utilization are of paramount importance to economic development and social progress. However, conventional approaches to mineral resource development and utilization are often characterized by significant resource wastage, prominent environmental pollution, and a high frequency of safety incidents, necessitating a fundamental transformation and upgrade (Zhou, 2023). The digital economy, an emerging economic paradigm driven by data elements and empowered by digital technologies, profoundly reshapes production methods, lifestyles, and governance across various sectors (Khan et al., 2024). It presents novel opportunities and challenges for the efficient and sustainable development of mineral resources.

The calculation of mineral resource efficiency encompasses a variety of methodologies, addressing aspects such as environmental and technical efficiency (Xiang et al., 2024). To prioritize environmental performance, researchers have developed innovative efficiency evaluation models. Notably, some scholars have introduced a non-radial directional distance function to independently and accurately measure the performance of water use and wastewater discharge (Zhou et al., 2019). Subsequently, the meta-Frontier was employed to assess the impact of technological heterogeneity on environmental benefits. On the other hand, other scholars utilized a pressure-state-response (PSR) model to comprehensively evaluate the ecological ramifications of mining activities across 134 prefecture-level mineral units in China. This framework considered three key perspectives–environmental impacts, ecological vulnerability, and ecological functions–to construct a holistic eco-efficiency evaluation framework (Ma et al., 2022). Alternatively, other scholars have concentrated on the technical efficiency of mineral resource development (Pan et al., 2024). Other researchers employed an input-output model to calculate the Malmquist index, analyzing the efficiency trends within the mining industry across 31 provinces in China from 2007 to 2016 (Chen et al., 2022). It highlighted the significant role of technological progress in driving improvements in mining efficiency.

In recent years, a surge in the adoption of digital technologies has occurred across the mineral resource sector. Applications such as smart exploration, smart mining, smart beneficiation, and mine safety monitoring have become increasingly prevalent, significantly improving operational efficiency and safety (Liu et al., 2022). This trend reflects a broader shift in the industry towards embracing digital solutions that enhance productivity and sustainability. Moreover, this shift is further reinforced by European Union (EU) legislation mandating energy efficiency enhancements, including the integration of energy storage systems and intelligent devices (Más and Kuiken, 2020). Such regulatory frameworks not only encourage the adoption of advanced technologies but also facilitate the transition towards more sustainable practices within the sector. Highlighting the potential of digital technologies to enhance resource management, some researchers employed a Difference-in-Difference (DID) model to investigate the impact of digital government initiatives on natural resource efficiency (Xu et al., 2024). These initiatives illustrate the effectiveness of digital tools in fostering greater resource efficiency at both governmental and industrial levels. Their findings indicated that the implementation of digital technologies within government operations led to enhanced efficiency in natural resource utilization.

Furthermore, studies have demonstrated the positive influence of big data and advancements in science, technology, and innovation on improving the efficiency of coal resource utilization (Zhang et al., 2023). Research also indicates a strong positive correlation between digital development and the volume of trade in mineral resources. Specifically, a 1% increase in digital development has been shown to correlate with an increase in the mineral resource trade volume of nearly 0.18% in the short term and 0.23% in the long term (Alsagr et al., 2024). However, contrasting research suggests that in some resource-depleted countries, particularly in certain African nations, the impact of high technology on resource utilization efficiency may be less pronounced (Zhang et al., 2023). Despite the growing body of research on the broader impacts of digital technologies on resource efficiency, there remains a relative scarcity of measurement methods specifically tailored to assess the utilization efficiency of mineral resources. Moreover, the academic community has yet to fully explore whether and how the development of the digital economy can comprehensively enhance the utilization efficiency of mineral resources across China's provinces and regions, including a detailed examination of the underlying influential mechanisms. These diverse methodologies demonstrate the multifaceted nature of mineral resource efficiency and the need for tailored approaches to accurately assess its various dimensions.

Consequently, investigating the impact of digital economy development on mineral resource utilization efficiency carries significant theoretical and practical implications for promoting the mining industry's transformation and achieving the dual goals of resource efficiency and sustainable development. However, given the significant regional disparities in economic development across China, it remains unclear whether the development of the digital economy can universally improve mineral resource utilization efficiency across all provinces and regions, and if so, through what mechanisms. To date, no specific research has addressed these questions comprehensively. This study addresses these questions by employing ordinary least squares (OLS) regression and the system generalized method of moments (system GMM) to quantify the impact of digital economy development on mineral resource utilization efficiency in China. Furthermore, it investigates the mediating roles of upgrading industrial structures and technological innovation in this relationship. Through the heterogeneity analysis, we investigate whether there is significant regional heterogeneity in the impact of digital economy development on the utilization efficiency of mineral resources in the eastern and central-western regions of China.

2 Theoretical analysis and research hypothesis

2.1 Digital economy development and mineral resource utilization efficiency

With its robust information integration and processing capabilities, the digital economy is revolutionizing resource allocation in traditional industries, including the mineral resources sector. By leveraging digital platforms and online trading systems, the digital economy optimizes resource allocation, promotes rational development, and enhances resource utilization, thereby injecting new vitality into the mining industry's pursuit of high-quality development (Liu et al., 2024; Wang et al., 2024).

One crucial way the digital economy contributes to this transformation is by optimizing resource allocation. Firstly, it fosters transparency and reduces information asymmetry, a common challenges in traditional mineral resource markets (Yang et al., 2024). The digital economy enhances market transparency, reduces search costs, and facilitates precise matching between suppliers and consumers by establishing digital information platforms that integrate supply and demand data. This mitigates the inefficiencies and resource waste associated with information asymmetry. Secondly, the digital economy facilitates the development of efficient price discovery mechanisms. Online trading platforms, streamlined transaction processes, and increased market participation contribute to the formation of fairer and more rational resource prices, guiding resources towards more productive applications (Alsagr et al., 2024). Furthermore, the inherently low marginal cost and cross-regional accessibility of digital technologies transcend geographical constraints, facilitating efficient resource allocation across regions. This fosters the flow of mineral resources from resource-rich areas to regions with high demand, enhancing regional economic coordination and development. Moreover, government agencies can utilize digital data to monitor and manage resource flows, optimizing allocation strategies and minimizing waste (Peng et al., 2023).

On the other hand, the digital economy is revolutionizing the mining industry by empowering all facets of the production process (Barnewold and Lottermoser, 2020). It fosters intelligent, automated, and refined management practices and significantly boosts efficiency, ultimately driving high-quality development within the sector. Firstly, it facilitates intelligent mining, leveraging technologies like the Internet of Things, artificial intelligence, and machine learning to enhance mining equipment, enabling remote control, autonomous operation, and intelligent decision-making, which results in increased efficiency, reduced labor costs, and improved safety (Jiao et al., 2024). Secondly, refined management powered by digital technologies optimizes production processes. Real-time data collection and processing provide valuable insights for decision-making. Sensors monitor equipment performance, ore grade, and output, enabling timely identification and resolution of production bottlenecks. Technologies like digital twins create virtual mine models for simulating and optimizing mining operations, leading to improved resource recovery and reduced costs. Thirdly, automation reduces reliance on manual labor, enhancing efficiency and lowering costs (Chen et al., 2020). Robots can perform repetitive tasks like ore sorting and loading, improving operational efficiency and safety. Automated control systems enable remote operation and autonomous functioning of mining equipment, minimizing human intervention.

Furthermore, the digital economy enhances safety and indirectly boosts productivity through real-time monitoring and early warning systems. Sensors monitor environmental parameters like gas concentration, temperature, and humidity, triggering alerts to prevent accidents. Video surveillance systems provide real-time oversight of operations, enabling prompt detection and resolution of safety hazards, minimizing downtime, and ultimately enhancing overall efficiency (Vještica et al., 2023). Finally, data-driven decision-making empowers management and drives further efficiency gains. Comprehensive data collection offers valuable insights into production efficiency, costs, and safety, enabling informed strategic decision-making.

Moreover, data analytics platforms facilitate the identification of patterns and trends, further supporting evidence-based decision-making and enhancing management effectiveness. Artificial intelligence can be employed for predictive analysis, optimizing production planning and equipment maintenance, enhancing management capabilities, and mitigating operational risks, ultimately leading to increased productivity (Ding et al., 2024). Therefore, Hypothesis one is proposed in view of the fact that the development of the digital economy optimizes the integration of mineral resources and improves the efficiency of production in all segments:

H1: Digital economic development can effectively improve the utilization efficiency of mineral resources.

2.2 Industrial restructuring: the brokering effect

The digital economy enhances mineral resource utilization efficiency by upgrading industrial structure, encompassing intra-industry and inter-industry advancements.

Intra-industry upgrading emphasizes the digital, intelligent, and green transformation of the mining industry itself, leading to optimized resource utilization within the sector. By empowering various stages of the mining production process, digital technologies unlock significant efficiency gains. In resource extraction, intelligent mining, enabled by technologies such as the Internet of Things, artificial intelligence, and machine learning, facilitates precise resource detection, extraction, and reduced waste, ultimately maximizing output (Xie et al., 2022). Real-time monitoring and data analysis, powered by advanced sensors and data platforms, streamline production processes, minimize energy and material consumption, and enhance overall resource utilization (Duarte et al., 2021). Furthermore, digital tools support environmental protection by monitoring pollution levels, facilitating timely interventions to curb emissions, and optimizing waste management strategies for enhanced resource recovery (Kurniawan et al., 2022). This further reflects the direct impact of the digital economy on mineral resource utilization efficiency.

On the other hand, inter-industry upgrading focuses on shifting the broader industrial structure from a resource-intensive paradigm to a technology-intensive one, thereby reducing reliance on mineral resources and fostering more efficient utilization across sectors. The digital economy fuels the growth of emerging industries, including high-end equipment manufacturing, advanced materials, and renewable energy (Zhou et al., 2021). These industries exhibit a demand profile that favors high-quality, processed resources over raw materials, thereby driving efficient resource use and diminishing overall dependence on mineral extraction (Gaimon and Morton, 2005). Moreover, the digital economy catalyzes the integration and development of diverse industries, fostering synergistic relationships between the mining, manufacturing, and services sectors. This integration leads to novel industrial forms and business models that optimize resource utilization across value chains. For instance, digital technologies facilitate collaboration between mining enterprises and equipment manufacturers to develop intelligent mining equipment, enhancing operational efficiency (Cheng et al., 2024). Similarly, partnerships between mining companies and logistics providers, enabled by digital platforms, optimize transportation schemes and reduce costs.

The digital economy fosters a trend towards resource-efficient and high-value industries, generating positive externalities for overall resource utilization. Based on this, Hypothesis 2 is proposed.

H2: Industrial structure upgrading mediates between digital economy development and mineral resource utilization efficiency.

2.3 Technological innovation: the brokering effect

The digital economy, characterized by its capacity to reduce information communication costs and amplify knowledge spillovers, effectively lowers the cost of scientific and technological research and development. The integration of digital finance has broadened financing channels, providing increased financial support for technological innovation and accelerating the translation of scientific and technological advancements into practical applications. Simultaneously, the adoption of digital technologies fosters a diversification of stakeholders in mining innovation, creating a more open and collaborative innovation ecosystem that fuels technological progress (Wang et al., 2023). Additionally, digital intelligence technologies enable precise identification of nuanced demands in mineral resource development and utilization, guiding innovation towards refined and personalized solutions and further invigorating scientific and technological innovation within the mining sector. Notably, green technology innovation emerges as a crucial component of mining science and technology innovation, playing a pivotal role in advancing the green and low-carbon transformation of the mining industry (Huang et al., 2024).

Technological innovation propelled by the digital economy, including green technological innovation, has yielded multifaceted improvements in mineral resource utilization efficiency, driving a green and low-carbon transition within the mining industry (Xue et al., 2024). The implementation of intelligent and green infrastructure has modernized traditional approaches to mineral resource development and utilization, fostered the establishment of green mines, and enhanced resource utilization efficiency. Scientific and technological advancements have catalyzed refined exploration and green development practices, expanding the scope of mineral resource development and utilization while mitigating negative environmental impacts. Moreover, the digital economy has spurred the greening and upgrading the mining industry's digital information infrastructure and facilitated the digitization, virtualization, and green transformation of mineral resource development and utilization (Priyadarshy, 2018). This has fostered multi-stakeholder synergistic innovation, amplified the comprehensive benefits derived from mineral resource development, and propelled the green and low-carbon development of the mining industry. Based on this, Hypothesis 3 is proposed.

H3: Technological innovation mediates the relationship between the development of the digital economy and the efficiency of mineral resource utilization.

Based on hypotheses 1 through 3, the specific impact of digital economic development on mineral resource utilization efficiency is illustrated in Figure 1.

3 Methods

3.1 Econometric modeling

3.1.1 Super-efficient SBM model

This research uses the super-efficient SBM model with non-expected output to measure the efficiency of mineral resource utilization. The calculation in Equation 1 (Tian et al., 2020):

$$Min(Eff) = \frac{\frac{1}{m}\sum_{i=1}^{m}(\bar{x}/x_{ik})}{\frac{1}{p_1+p_2}\left(\sum_{s=1}^{p_1}\bar{y}^d/y^d_{sk} + \sum_{q=1}^{p_2}\bar{y}^u/y^u_{qk}\right)}$$

$$\begin{cases} x \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j; \bar{y}^d \leq \sum_{j=1,\neq k}^{n} y^d_{sj}\lambda_j; \bar{y}^u \geq \sum_{j=1,\neq k}^{n} y^u_{qj}\lambda_j \\ \bar{x} \geq x_k; \bar{y}^d \leq y^d_k; \bar{y}^u \geq y^u_k \\ \lambda_j \geq 0, i = 1, 2, \cdots, n, j \neq 0 \\ s = 1, 2, \cdots, p_1; q = 1, 2, \cdots, q_2 \end{cases} \tag{1}$$

where Eff represents the efficiency value, the analysis encompasses n decision-making units (DMUs), specifically 30 Chinese provinces and cities. Each DMU utilizes m inputs, produces p_1 desired outputs, and generates p_2 undesirable outputs. x, y^d, and y^u denote the corresponding elements within the input matrix, desired output matrix, and undesirable output matrix, respectively.

3.1.2 Baseline model

To verify H1, a benchmark model is constructed for the direct impact of the digital economy on mineral resource utilization efficiency:

$$Eff_{it} = \alpha_0 + \alpha_1 Dig_{it} + \delta X + u_i + \eta_t + \varepsilon_{it} \tag{2}$$

where Eff_{it} is the mineral resource utilization efficiency of province (district, city) i at time t, Dig_{it} is the level of digital economic development of province (district, city) i at time t. The vector X represents a series of control variables, u_i denotes individual fixed effects, η_t denotes time fixed effects, and ε_{it} represents a random disturbance term.

As the mineral resource efficiency is related to the previous cumulative development of individual provinces, the current economic efficiency of the mineral resource is closely related to the total amount of minerals, technology, and environment of each place in the previous years. Because of this, this research also considers adding the lagged one-period city economic toughness level for systematic GMM regression (Da Silva and Cerqueira, 2017). In order to solve the problem of model estimation bias caused by the correlation between the lagged term and error term of the dependent variable in Equation 3.

$$Eff_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 Eff_{it-1} + \delta X + u_i + \eta_t + \varepsilon_{it} \tag{3}$$

where E1 is the lagged period of mineral resource efficiency. The remaining symbols have the same meaning as in Equation 2.

3.1.3 Mediation effects model

This study employs a sequential mediation analysis approach to test Hypothesis 2 (H2) and investigate the potential mediating

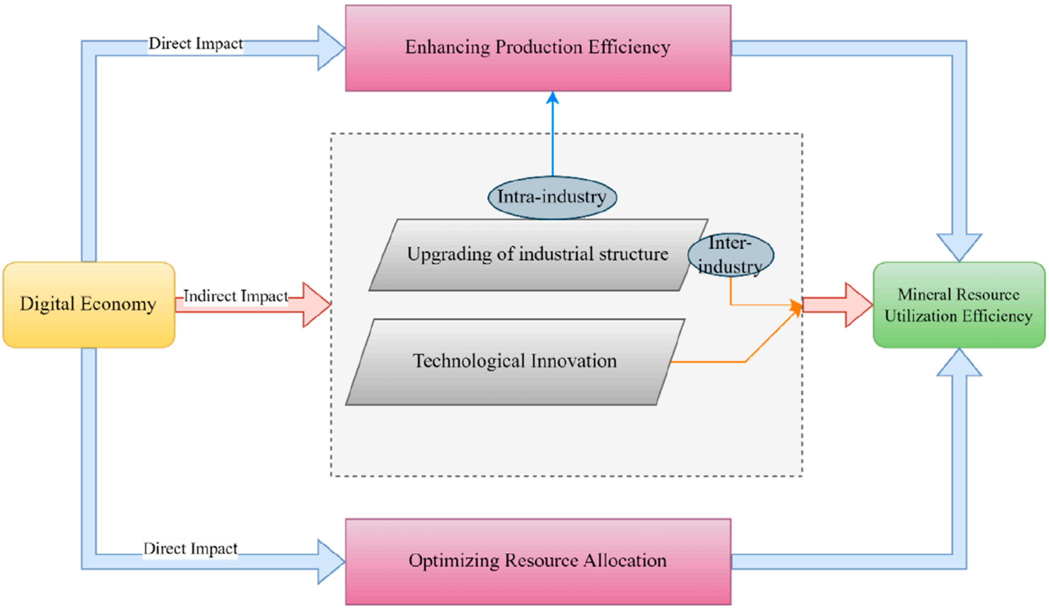

FIGURE 1
Mechanism of the digital economy on the utilization efficiency of mineral resources.

mechanism through which the digital economy influences mineral resource utilization efficiency. Building upon the benchmark regression model, the mediating variable of industrial structure upgrading is introduced to construct a mediation effect model examining the relationship between the digital economy and mineral resource utilization efficiency:

$$Asi_{it} = \beta_0 + \beta_1 Dig_{it} + \delta X + u_i + \eta_t + \varepsilon_{it} \tag{4}$$

$$Eff_{it} = \gamma_0 + \gamma_1 Dig_{it} + \gamma_2 Asi_{it} + \delta X + u_i + \eta_t + \varepsilon_{it} \tag{5}$$

the Asi in Equations 4, 5 represents the mediating variable of industrial structure upgrading, and other variables are the same as those in the baseline model.

In order to verify H3, based on the benchmark regression, the mediating variable of technological innovation upgrading is introduced to construct a test model of the mediating effect of the digital economy on the utilization efficiency of mineral resources.

$$Tec_{it} = \beta'_0 + \beta'_1 Dig_{it} + \delta X + u_i + \eta_t + \varepsilon_{it} \tag{6}$$

$$Eff_{it} = \gamma'_0 + \gamma'_1 Dig_{it} + \gamma_2 Tec_{it} + \delta X + u_i + \eta_t + \varepsilon_{it} \tag{7}$$

Tec in Equations 6, 7 represents the mediating variable of technological innovation, and the other variables are the same as in the baseline model.

3.2 Variable definition and measurement

3.2.1 Dependent variable

The explanatory variable is the utilization efficiency of mineral resources; referring to Tone's research (Tone, 2001), the efficiency measurement in this research uses the super-efficient SBM model. Input indicators include labor, capital, and mineral resource inputs. Output indicators include provincial (regional and municipal) GDP, industrial solids, and carbon dioxide emissions. Among them, GDP is the desired output, and industrial solid and carbon dioxide emissions are non-desired outputs (Yu et al., 2015).

3.2.2 Explanatory variable

The explanatory variable is the digital economy, and the related measurements have not yet been standardized.

With reference to the digital economy indicator system released by the China Academy of Information and Communication Technology and the National Bureau of Statistics, and considering the continuity and long-term observability of data, this research comprehensively evaluates the level of digital economy development at the provincial level in four aspects: digital infrastructure, digital informatization, digital industrialization, and digital finance. At the same time, in order to reflect the relative advantages and disadvantages of the digital economy and the ranking of the level, the entropy weight-TOPSIS method is comprehensively applied to measure the level of development of the digital economy concerning the previous studies (Dong et al., 2022; Li et al., 2023).

3.2.3 Intermediary variable

The mediating variable is industrial structure upgrading, which is measured by the index of industrial structure advancement (Li et al., 2023). It is manifested in transforming industrial structure from low value-added labor-intensive industries to high value-added capital-intensive and technology-intensive industries. It is also manifested in the continuous optimization and upgrading of industrial structure and the improvement of industrial competitiveness. In this research, the advanced industrial structure is obtained by dividing the added value of the tertiary industry and the added value of the secondary industry (Ran et al., 2023).

The second mediating variable is technological progress. Technological progress is a decisive factor in the quality of economic development, and the number of patents authorized for green technology is an important indicator of the results of economic transformation, reflecting the breakthroughs and progress made in green technology (Du et al., 2019). Therefore, this research adopts the *per capita* green technology patent authorization of provinces (autonomous regions and municipalities) as a measure.

3.2.4 Control variable

The main control variables selected in this research include foreign trade dependence, R&D intensity, fiscal concentration, marketization level, and asset level. Table 1 shows the detailed definitions of the variables (Lu and Zhao, 2024; Wei, 2024; Xia et al., 2024).

3.3 Data sources and descriptive statistics

This research selects 360-panel data from 30 provinces in mainland China from 2011 to 2022 (Tibet, Hong Kong, Macao, and Taiwan are excluded in consideration of the availability and completeness of the data). The data are obtained from the China Statistical Yearbook, China Energy Statistical Yearbook, statistical yearbooks, and bulletins of provinces (autonomous regions and municipalities). Individual missing values are completed by interpolation. In order to avoid large differences in values due to differences in units, the total assets of all state-owned and non-state-owned industrial enterprises above the designated size (Asset) and the number of all state-owned and non-state-owned industrial enterprises above the designated size (Firm) are logarithmized. Descriptive statistics are tabulated below (Table 2).

4 Results and discussion

4.1 Empirical findings and discussion

4.1.1 Benchmark regression

In this section, we examine the impact of the digital economy (Dig) on the efficiency of mineral resource utilization (Eff) at a holistic level. To ensure the robustness of our findings, both Ordinary Least Squares (OLS) regression and System Generalized Method of Moments (System GMM) are employed. OLS is straightforward and provides consistent estimates under certain assumptions; however, it may suffer from issues related to endogeneity and omitted variable bias, which can lead to inaccurate conclusions. In contrast, System GMM is particularly useful in addressing these concerns by incorporating lagged dependent variables as instruments, thus allowing for the analysis of dynamic relationships.

Examining the impact of the digital economy (Dig) on the efficiency of mineral resource utilization (Eff) at a holistic level, the results of the benchmark regressions are reported in Table 3. Column (1) presents the OLS regression results. Column (2) presents the results of the systematic GMM regression considering one period lag. Examining the impact of the digital economy (Dig) on the efficiency of mineral resource utilization (Eff) at a holistic level, the results of the benchmark regressions are reported in Table 3. According to the data in column (1), the coefficient of mineral resource utilization efficiency is 0.161 and is significant at the 1% level. This indicates that the digital economy has significantly improved the utilization efficiency of mineral resources. According to the results in column (2), there is also a positive relationship between the level of development of the digital economy and the utilization efficiency of mineral resources; that is, for every 10% increase in the level of development of the digital economy, the utilization efficiency of mineral resources will be increased by about 2.26% accordingly. H1 is proved. At the same time, it can be seen that the lagged period efficiency (L.Eff) of mineral resources has a significant role in promoting the efficiency of mineral resources utilization in the current period, and its coefficient is 0.168 at the 10% significance level. These findings are consistent with previous research that the development of the digital economy accelerates mineral trade (Alsagr et al., 2024) and reduces carbon emissions (Zuo et al., 2022), thereby increasing the efficiency of mineral resources.

Regarding the regression results of control variables, scientific research intensity, marketization level, and asset level have significant effects on the utilization efficiency of mineral resources in each province (autonomous region and city).

4.1.2 Analysis of intermediation effects

In order to analyze the role of "digital economy (Dig) - industrial structure upgrading (Asi) - mineral resources utilization efficiency (Eff)", this research adopts the causal step-by-step regression method to verify the effect of "digital economy (Dig) - industrial structure upgrading (Asi) - mineral resources utilization efficiency (Eff)". According to the regression results in Table 4, it can be seen that the regression coefficients in column (1) are consistent with those in the previous article. The regression coefficient of column (2) is 0.018, which is positive at a 10% significance level, indicating a strong positive correlation between the level of digital economy development and industrial structure upgrading. The test results in column (3) show that industrial structure upgrading positively affects the utilization efficiency of mineral resources, with a coefficient of 0.119, which is significant at a 5% significance level. Compared with the baseline regression data, the digital economy (Dig) coefficient decreases from 0.161 to 0.134 after adding industrial structure upgrading, indicating that industrial structure upgrading plays the role of mediating effect in promoting mineral resource utilization efficiency by the digital economy.

The wave of the digital economy sweeping the world has not only given rise to booming digital industries, such as the Internet, e-commerce, and software development, but has also profoundly affected the transformation and upgrading of traditional industries, and the mineral resources industry is no exception. The digital economy promotes the digital transformation of traditional industries by empowering them, thus enhancing the utilization efficiency of mineral resources and realizing a win-win situation regarding economic and environmental benefits.

Specifically, by digitizing traditional production processes, business models, and management methods, enterprises introduce information technology and digital tools to realize digital

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TABLE 1 Definition of main variables.

Level 1 indicators	Level 2 indicators	Level 3 indicators	Level 4 indicators	Calculation or meaning	unit
Dependent Variable	Green Utilization Efficiency of Mineral Resources (Eff)	Inputs	Labor input	Employed population at the end of the year	million people
			Fixed capital stock	Investment in fixed assets	Billion dollars
			Mineral Resources Inputs	Total energy consumption and limestone and iron ore output combined	—
		Outputs	GDP	Gross Regional Product	Billion dollars
			CO2 emissions	CO2 emissions	tons
			General industrial solids emissions	General industrial solid emissions	million tons
Core explanatory variables	Level of the digital economy (Dig)	Digital Infrastructure	Fiber optic cable lines per capita		Kilometers/million people
			Cell phone penetration rate	Cell phone subscribers/year-end resident population	Department/100 people
			Internet domain names per capita	Internet broadband access subscribers/year-end resident population	
		Digital Information Levels	Internet penetration rate		%
		Digital Industrialization	Percentage of employees in information service industry	Employment in urban units of the information transmission, software and information technology services industry as a proportion of the total employed population	Household/person
			Software Business Revenue as a Percentage of GDP		%
		Digital Finance Level	Digital Finance Digitization Degree		—
Mediating variables		Industrial Upgrading (Asi)	Index of Industrial Advancement	Value added of tertiary industry/value added of secondary industry	—
		Technological Innovation (Tec)	Green Technology Patent Authorization per Capita	Green technology patent authorization per 10,000 people	cases/10,000 people
Control variables		Foreign Trade Dependence		Foreign Direct Investment/GDP	%
		R&D Intensity		Science and Technology Expenditure/GDP	%

(Continued on the following page)

TABLE 1 (*Continued*) Definition of main variables.

Level 1 indicators	Level 2 indicators	Level 3 indicators	Level 4 indicators	Calculation or meaning	unit
		Financial Concentration		Local Per Capita Fiscal Expenditure/(Local Per Capita + Central Per Capita)*100	%
		Marketization Level		Marketization Index	—
		Asset level		Logarithm of total assets of all state-owned and non-state-owned industrial enterprises above scale	—
				Logarithm of the number of all state-owned and non-state-owned industrial enterprises above scale	—

TABLE 2 Descriptive statistics.

Variable	Obs	Mean	Std. Dev	Min	Max
Eff	360	0.599	0.375	0.096	1.459
Dig	360	0.426	0.080	0.291	0.706
Asi	360	1.354	0.745	0.527	5.283
Tec	360	0.913	1.221	0.026	8.681
Foreign Trade Dependence	360	0.026	0.042	0.000	0.576
Financial Concentration	360	86.059	3.632	78.582	93.683
Marketization Level	360	8.107	1.945	3.36	12.922
R&D Intensity	360	2.171	1.517	0.400	6.800
lnFirm	360	8.812	1.215	4.796	11.056
lnAsset	360	10.111	0.838	7.466	11.926

TABLE 3 Benchmark regression results.

Variables	(1)	(2)
	Eff	Eff
L.Eff		0.168*
		(0.0901)
Dig	0.161*	0.226*
	(0.0935)	(0.130)
Foreign Trade Dependence	−0.533	2.241
	(−1.489)	(1.646)
R&D Intensity	−0.00723	0.0974**
	(−0.0328)	(0.0459)
Financial Concentration	0.0253	−0.00686
	(0.0160)	(−0.0246)
Marketization Level	0.0491**	−0.0772**
	(0.0227)	(−0.0343)
lnFirm	0.203**	0.0468
	(0.0846)	(0.0850)
lnAsset	−0.129	0.0554
	(−0.0821)	(0.142)
Constant	−2.493	0.385
	(−1.669)	(2.334)
Observations	360	360
Number of id	30	30

Robust standard errors in parentheses.
***p<0.01,**p<0.05,*p<0.1.

management and automated operations in production, supply chain, customer relations, and other aspects (Wang et al., 2023). For instance, intelligent mining technologies enable precise exploration and efficient extraction of mineral resources, minimizing resource waste and environmental pollution (Cacciuttolo et al., 2023). Digital supply chain management systems optimize the procurement, transportation, and sales of mineral resources, reducing operating costs (Yin and Zhao, 2024). Furthermore, real-time monitoring systems facilitate comprehensive tracking and oversight of product quality, enhancing product quality and stability.

Digital technology also promotes the linkage between mineral resources-related industries, i.e., secondary and tertiary industries, and accelerates the upgrading of industrial structures. This is consistent with previous research findings (Lin et al., 2023; Sinclair and Coe, 2024) that the transfer of mineral resources from low-

TABLE 4 Mediated effects test.

Variables	(1)	(2)	(3)	(4)	(5)
	Eff	Asi	Eff	Tec	Eff
Dig	0.161*	0.018*	0.134	1.049***	−0.0918
	(0.0935)	(0.00941)	(0.0956)	(0.246)	(0.179)
Asi			0.119**		
			(0.0496)		
Tec					0.102***
					(0.0288)
Constant	−2.493	0.149	−2.104	−5.089***	−2.789***
	(1.669)	(0.297)	(1.614)	(1.202)	(0.668)
Control Variable	YES	YES	YES	YES	YES
Observations	360	360	360	360	360
Number of id	30	30	30	30	30

Robust standard errors in parentheses.
***$p<0.01$, **$p<0.05$, *$p<0.1$.

productivity sectors or industries to high-productivity sectors or industries can promote the improvement of the utilization efficiency of mineral resources in the entire national economic sector. Therefore, upgrading industrial structures can serve as an important transmission path for the digital economy and influence the utilization efficiency of mineral resources.

Empirical studies have also confirmed the path of "digital economy development (Dig)-industrial structure upgrading (Asi)-mineral resources utilization efficiency improvement (Eff)", in which industrial structure upgrading plays an important intermediary role. This means that the improvement of the level of digital economy development can promote industrial structure upgrading and then improve the utilization efficiency of mineral resources. H2 is proved.

In order to analyze the role path of "digital economy (Dig)-j technology innovation (Tec)-mineral resource utilization efficiency (Eff)," this research adopts the causal step-by-step regression method to verify the role effect of this path. According to the regression results in Table 4, it can be seen that the regression coefficients in column (1) are consistent with the regression coefficients in the previous article. The regression coefficient in column (4) is 1.049, which is positive at a 1% significance level, indicating a strong positive correlation between the level of digital economy development and technological innovation. The test results in column (5) show that technological innovation positively affects mineral resource utilization efficiency with a coefficient of 0.102, significant at the 1% significance level. Compared with the baseline regression data, the digital economy (Dig) coefficient is no longer significant after adding industrial structure upgrading. This indicates that technological innovation plays the role of mediating effect in the digital economy process to promote the improvement of mineral resource utilization efficiency.

The digital economy is driving the green transformation of traditional industries with its powerful force, and the mineral resources industry is no exception (Wang et al., 2024). First, intelligent mining has become a reality. The combination of digital technology and automation equipment has promoted intelligence and unmanned mining. The application of intelligent equipment, such as uncrewed mining cars and remote control drilling rigs, reduces human interference, improves mining efficiency, reduces safety risks, and minimizes damage to the mining environment. Secondly, precise management has become possible. The application of the Internet of Things, sensors, and other technologies has realized the real-time monitoring of mine environmental parameters, which provides data support for the precise management of the mine environment. Mine managers can keep abreast of mine environmental conditions and discover and deal with potential environmental problems, such as groundwater pollution and surface subsidence, to minimize environmental risks and reduce pollutant emissions. It also reduces the government's costs of supervising the pollution emissions of relevant enterprises. Finally, resource recycling is effectively promoted. Digital technology can build a recycling platform for mineral resources to promote the recovery and reuse of mine waste, tailings, and other resources. Through the digital management system, the generation, treatment and reuse of mine waste can be tracked to improve resource utilization, reduce environmental pollution, and realize the green recycling development of mineral resources (Liang et al., 2024). Thus, the utilization efficiency of mineral resources can be effectively improved. H3 is proved.

4.2 Robustness tests

In order to exclude possible endogeneity problems between the digital economy and mineral resource utilization efficiency and to enhance the reliability of the above conclusions, this research discusses endogeneity and conducts robustness tests from the following aspects.

(1) Instrumental variables approach. In order to reduce the endogeneity problem, this research refers to the study of Nunn and Qian (Nunn and Qian, 2014) and adopts the interaction term between the ratio of employees in the information service industry and the Internet penetration rate of provinces (autonomous regions and municipalities) as the instrumental variable (IV) of digital economy development, and uses the two-stage least squares (2SLS) method to analyze the endogeneity.
(2) Replacement of core explanatory variables. This research replaces the original system of indicators for measuring the digital economy and adopts a separate indicator to measure it. In order to verify the reliability of the estimation results, the benchmark model is further re-estimated by using the proportion of total telecom business to GDP as a proxy for the digital economy.
(3) Shorten the sample period. Since China's Broadband China strategy was launched in 2013, the original sample period has been shortened from 2011 to 2022 and 2013 to 2022. As shown in Table 5, the sign and significance of the

TABLE 5 Endogeneity and robustness tests.

Variables	(1)	(2)	(3)
	Eff	Eff	Eff
L.Eff		0.167**	0.199**
		(0.0662)	(0.0973)
Dig	3.684***	0.810***	0.315**
	(1.424)	(0.297)	(0.135)
Constant	−3.953***	0.719	−0.182
	(1.009)	(1.657)	(2.444)
Control Variable	YES	YES	YES
Observations	360	360	202
Number of id	30	30	30

Robust standard errors in parentheses.
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

coefficients of the core explanatory variable, digital economy, do not change significantly compared with the basic regression results, which indicates that the above results are still robust after considering endogeneity.

4.3 Further discussion: Heterogeneity tests

The above baseline regression analysis shows that the development of the digital economy can significantly promote the efficiency of mineral resource utilization in Chinese provinces (autonomous regions and municipalities), and the regression results are still significant through the endogeneity and robustness tests. Due to the apparent differences in the level of economic development and the construction of digital infrastructure in different regions of China, it is still to be tested whether the digital economy can positively promote water resource utilization efficiency in different regions. Therefore, this research divides the sample provinces (autonomous regions and municipalities) into eastern, central, and western regions for group regression tests to further verify the heterogeneity of the impact of the digital economy on the utilization efficiency of mineral resources. The data in column (1) of Table 6 are the results for the Eastern region. Column (2) shows the results for the central and western regions. The results show that the estimated coefficients and significance levels of the digital economy are significantly different in different regions.

From column (1), the coefficient of the impact of digital economic development on mineral resource utilization efficiency in the eastern region is −0.389, which does not pass the significance test, indicating that the development of digital economy in this region has no promotional effect on the utilization efficiency of mineral resources in this region. Analyze the possible reasons for this being limited by the impact of mineral resource endowment and industrial structure transformation and upgrading. On the one hand, the eastern region is relatively scarce in mineral resources, the scale of mining development is small, and its contribution to economic growth is limited, resulting in a relatively weak impact of the digital economy on the utilization efficiency of mineral resources (Zuo et al., 2022). On the other hand, the eastern region has a higher level of economic development, the tertiary industry dominates the industrial structure, and the mining industry accounts for a relatively low proportion. The digital economy mainly promotes the development of the service industry, but it has a limited driving effect on the mining industry. In addition, part of the eastern region is undergoing industrial transformation and upgrading, gradually eliminating highly polluting and energy-consuming traditional industries, including some mining enterprises, resulting in a decline in the production of mineral resources, which also affects the improvement of the utilization efficiency of mineral resources.

TABLE 6 Heterogeneity test.

Variables	(1)	(2)
	Eff	Eff
Dig	−0.389	0.180*
	(0.363)	(0.0963)
Constant	−3.538	−3.624**
	(2.665)	(1.808)
Control Variable	YES	YES
Observations	107	185
Number of id	11	19

Robust standard errors in parentheses.
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

By column (2), the coefficient of the impact of digital economic development on mineral resource utilization efficiency in the central and western regions is 0.180, which passes the test of significance, indicating that the development of the digital economy in this region again has a promotional effect on the utilization efficiency of mineral resources in this region. Compared with the eastern region, the central and western regions in the wave of the digital economy, mineral resources utilization efficiency has achieved significant improvement, which may be due to the following reasons (Feng et al., 2023). First, the central and western regions are endowed with rich mineral resources and important energy and raw material bases in China, with great potential for mining development. The application of the digital economy can effectively improve the development and utilization efficiency of mineral resources, providing a strong impetus for the economic growth of the mining industry. Secondly, the proportion of traditional industries in the central and western regions is relatively high, and the mining industry is an important pillar of the industry that needs transformation and upgrading. The digital economy can promote the transformation and upgrading of the mining industry, improve the competitiveness of mining enterprises, and promote regional economic development. Third, national and local governments attach great importance to the development of the central and western regions and have introduced a series of policies and measures to support the development of the digital economy in the central and western regions and to promote the integration of digital technology and the mining industry, which creates a good policy environment for the digital transformation of the mining industry. In addition, the central and western regions started late in digital transformation. Still, they can learn from the lessons of the eastern region to avoid detours and achieve leapfrog development. Some mining enterprises in the central and western regions have actively embraced new technologies and vigorously pushed forward digital transformation, achieving remarkable results and setting an example for other enterprises.

5 Conclusions and policy implications

5.1 Conclusions

In the context of China's high-quality economic development being constrained by the mineral resources problem, and the state vigorously promotes the "Digital China" strategy, how to utilize the development of the digital economy to efficiently improve the utilization efficiency of mineral resources in China's provinces (districts and municipalities) has become an important and realistic issue.

This research takes the panel data of 30 provinces (autonomous regions and municipalities) in China from 2011 to 2022 as the sample. Firstly, the entropy weight-TOPSIS is used to calculate the index of the development level of the digital economy. Secondly, the non-radial and non-angle super-efficiency SBM model is used to calculate the efficiency of the utilization of mineral resources. Based on the above data, the mediation effect method is used to test the impact and effect of the digital economy on the utilization efficiency of water resources. Based on the above data, finally, the mediation effect method is used to test the impact and path of the digital economy on mineral resources utilization efficiency. The main conclusions are as follows:

The development of the digital economy can significantly improve the utilization efficiency of mineral resources in Chinese provinces (autonomous regions and municipalities). The conclusion is valid in both the OLS model and the systematic GMM model. In addition, the system GMM model verifies that the mineral resources utilization efficiency is time persistent, i.e., the value of the previous period will have an impact on the value of the current period. Specifically, the coefficient for the impact of the digital economy on mineral resource utilization efficiency is 0.161.

The analysis of intermediary effects shows that the development of the digital economy in Chinese provinces (autonomous regions and municipalities) can improve the utilization efficiency of local mineral resources by promoting industrial structure upgrading and technological progress. First of all, it shows that the development of the digital economy not only promotes a high level of industrial structure but also strengthens the links between industries, and the more reasonable industrial layout improves the utilization efficiency of mineral resources. Secondly, it shows that the development of the digital economy significantly improves local technological innovation, especially green technological innovation. In turn, the innovation results are applied to mineral resource-related industries, which reduces costs and efficiency and reduces pollution output, thus improving the utilization efficiency of mineral resources.

Heterogeneity analysis shows that due to the different mineral resource endowment advantages and industrial bases in eastern and central-western China, there is more obvious regional heterogeneity in the impact of the digital economy development level on the utilization efficiency of mineral resources. In the central and western regions play a significant role, with a coefficient of 0.180 at the 10% significance level.

5.2 Policy recommendations

To fully leverage the digital economy in enhancing mineral resource utilization, we recommend strengthening digital infrastructure, promoting digital technology and mining integration, and fostering a supportive policy environment. This involves investing in digital infrastructure in less developed regions, encouraging the adoption of technologies like cloud computing and big data in mining, and supporting collaboration between mining and tech companies. Simultaneously, policies should incentivize digital transformation in mining, increase R&D funding, and cultivate a skilled digital workforce.

Furthermore, the digital economy can drive industrial upgrading and resource efficiency by facilitating the shift towards high-efficiency industries, extending value chains, and fostering industry integration. For instance, it can promote the development of mineral processing and high-end manufacturing, reducing reliance on raw materials and enhancing resource utilization.

The digital economy can also spur green technological innovation. Big data analytics can optimize production processes, AI can develop green materials and processes, and blockchain can enhance supply chain transparency and resource recycling. These technologies can minimize environmental impacts and promote sustainable mining practices.

5.3 Research limitations

This study examines the impact of the digital economy on the utilization efficiency of mineral resources in China, and despite the results achieved, there are still some limitations. First, the study relies on publicly available statistical data, the accuracy and completeness of which may be limited, and the lack of exhaustiveness or timeliness of the data in certain regions may affect the reliability of the analyzed results. Second, although regional differences in the east, center and west were taken into account, it failed to fully explore the potential impact of local policies, cultural differences and other unique factors on the relationship between the development of the digital economy and the efficiency of resource utilization. Future research could explore in depth how the digital economy affects resource utilization efficiency through specific mechanisms such as technological innovation and industrial upgrading, and consider expanding the sample and timeframe to obtain more comprehensive conclusions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YT: Conceptualization, Methodology, Software, Visualization, Writing–original draft, Writing–review and editing. MiC: Formal Analysis, Software, Visualization, Writing–review and editing. WY: Formal Analysis, Visualization, Writing–review and editing. XW: Conceptualization, Formal Analysis, Investigation, Methodology, Visualization, Writing–original draft. Mac: Resources, Supervision, Validation, Writing–review and editing. WL: Conceptualization, Formal Analysis, Methodology, Resources, Supervision, Visualization, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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