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RESEARCH ARTICLE

Quantitative Analysis for Identifying the Role of Artificial Intelligence in Enhancing Competitiveness in China's Mining Sector

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ABSTRACT

With the increasing competitive pressure, AI solutions such as predictive maintenance, automation, and real-time monitoring have emerged as effective tools for the mining companies in China to enhance their operational efficiency which also reflects positively on competitiveness. This study aimed to investigate the impact of AI on the competitiveness of the mining industry in China with the mediating role of operational efficiency and moderating role of form size. A cross-sectional research design was employed, collecting data from 150 respondents through a close-ended questionnaire based on the TOE framework. The results revealed that AI implementation can positively impact the competitiveness of mining firms in China as it directly enhances the operational efficiency of the company which is instrumental for competitiveness. Here, the form size impacts the level of adoption of AI in firms as larger firms have more resources to implement AI in the company while smaller forms may have to focus on targeted operations due to resource constraints. In a nutshell, it can be said that AI implementation has a positive impact of the competitiveness of the mining industry in China.

INTRODUCTION

With the rise of digital technologies, artificial intelligence has emerged as a factor of efficient change for mining industries with predictive maintenance, automation, and real-time monitoring technologies. According to Zvarivadza et al. (2024), AI-driven technologies are reshaping the mining industry but changing its operational landscape by enabling smart decision-making, resource optimisation, and enhanced safety measures. The critical inefficiencies in the mining industry include sustainability issues and safety issues. Here, AI has strengthened the industry's competitiveness by enhancing operational efficiencies (Mistry et al., 2022). As a result, the adoption of AI in the mining industry has increased at a CAGR of 10% from $634.9 million in 2019 to $767.9 million in 2021 (Global Data, 2025). The transformative potential of AI creates efficient pathways for mining businesses to improve their operations aligned with environment and safety standards at low cost which reflects positively on company competitiveness. However, there may be a gap in understanding the specific ways AI impact the competitiveness of the mining industry in China globally which creates a foundation for this study.

The mining industry in China serves as a cornerstone for its economic development globally. According to Textor (2024), with more than 1500 mining operations, the mining industry contributed almost 1.5% share of the total GDP of China. This share of contribution increased significantly as in 2023, the added value of the mining industry in GDP increased by 2.3% year-on-year growth (Huld, 2024). This means that in China mining industry has critical importance to serve as the major contributor to the economy. China is a leading producer of critical minerals such as rarer earth elements accounting for 55-70% of mining and up to 90% of the processing (Singh, 2025). Similarly, China has 8% of the global lithium reserves with 72% of the refining capacity (Mine, 2024). The monopoly of China over lithium is a concern due to the increasing consumption of lithium for electric vehicles. However, to maintain this monopoly and global competitiveness China needs to address challenges such as the environmental effects of mining. The adoption of AI by Chinese mining companies such as Jianxi Copper, Zijin Mining Group, and many more can be a catalyst for enhancing safety, efficiency, and environmental sustainability. Consequently, AI-driven techniques and tools can reshape the factors of competitiveness in the Chinese mining industry.

Safety issues and high ecological prints are some of the critical factors which can impact the efficiency of mining companies (Yang et al., 2021). Here, the competitive pressure and increasing demand for lithium and such elements due to the promotion of electric vehicles create troubles for mining companies to enhance their refining capability which may not be addressed by traditional methods of mining. Consequently, the integration of AI in the mining industry has unlimited opportunities for mining companies to enhance efficiency with techniques such as predictive maintenance and data visualisation. Such innovative techniques driven by the power of AI can help the mining companies to create informed decisions and resource optimisation which can also reduce the cost of operations. However, empirical studies in this aspect mostly focused on developed countries while China is in the leading position globally. Therefore, this study contributes significantly to academic knowledge and industry practice to understand the impact of AI on industry competitiveness and also offers practical insights for the management of mining operations to integrate AI to achieve strategic objectives. The scope of this study is limited to the mining industry in China with a focus on AI-driven technologies such as predictive maintenance, automation, and real-time monitoring. This research also investigates both the direct and indirect impacts of AI on competitiveness, emphasizing operational factors as mediators and firm size as a moderating variable.

Research aim

This research aims to investigate the impact of Artificial Intelligence on the competitiveness of the mining industry in China.

Research questions

1. How does the AI influence the competitiveness of the mining industry in China?
2. How AI-driven technologies can enhance operational efficiency of mining companies?
3. Does the size of the mining company impact the adoption of AI in the mining process?

Research objectives

1. To investigate the impact of AI on the competitiveness of mining companies
2. To identify the impact of operational efficiency on the competitiveness of the mining companies
3. To explore the impact of the firm size on the adoption of AI in mining operations.

LITERATURE REVIEW

Artificial intelligence and competitiveness in mining

The transformative potential of AI-powered tools and techniques such as automation, predictive maintenance, and real-time monitoring can enhance the performance of mining companies effectively. In this context, Arinze et al. (2024), comprehend that AI has high computational power and statistical information which can help to create informed decisions and enhance the operational efficiency of the company. Balcıoğlu et al. (2024), also mentioned that AI tools and techniques can improve the safety and sustainability paradigm in mining operations due to data processing and visualisation which helps to make informed decisions. Consequently, the integration of AI in mining operations can positively reflect on operational efficiency as it can handle issues such as safety and sustainability which cannot be addressed by traditional mining processes. Here, predictive maintenance to enhance equipment efficiency, automation to streamline routine tasks, and real-time monitoring for optimisation have been largely adopted by companies in the mining industry. It means that management in the mining companies can gain a competitive advantage by leveraging innovative techniques of AI which lead to innovative solutions to address the critical challenge in the mining industry.

The mining industry in China operates under increasing competitive pressure. According to Textor (2024), China has a total of 1500 mining operations out of which three-quarters are located underground. However, at the global level, due to dominance over processing in several critical minerals such as lithium, cobalt, and rare earth elements, China has high competitiveness (Andrews, 2023). Here, the competitiveness of the mining industry in China can be attributed to advanced technologies. Si (2023) reported that mining operations in China leverage advanced telecommunications and artificial intelligence technologies such as cutting-edge automation and unmanned solutions which redefine the mining companies with smart makeover. Consequently, the innovative solutions driven by AI helped the mining operations to gain market leadership, profitability, and efficiency. However, mining companies in China also have challenges such as the geo-political war between China and the US to access the abundant natural resources of Africa (Byamungu, 2022). This global competition for the rights for mining not only impacts investment, trade policies, and political alliances but also creates a necessity for mining companies to opt for innovative technology such as AI to enhance operational efficiency. This operational efficiency of the Chinese mining industry can perpetuate the competitiveness of the industry by improving refining techniques and mining operations. Based on these insights, the first hypothesis is generated:

H1: Artificial Intelligence (AI) positively influences Competitiveness in the mining sector.

Impact of AI on operational efficiency

According to Obiki-Osafiele et al. (2024), operational efficiency refers to the dynamic capabilities of the company such as resources, decision-making, and many more which are critical to attaining organisational goals. Consequently, AI-driven technologies can enhance operational efficiency of mining companies by adding value to the dynamic capabilities of the companies such as resource optimisation, and informed decision-making supported by AI can enhance the firm’s capability to improve the refining process. Here, Handoyo et al. (2023), opined that with better operational processes, mining companies with AI can deliver high value to the consumers. With low cost and high efficiency, the AI tools reflect positively on the competitive position of the company. For example, with automation, AI can help mining companies improve product quality which is critical for managing stakeholders' expectations. Therefore, it can be said that AI enhance the operational efficiency of the companies which reflects positively on the competitive position of the company.

H2: Operational Efficiency mediates the relationship between Artificial Intelligence (AI) and Competitiveness.

The factors of operational efficiency such as cost, safety, innovation, and sustainability can be the main factors influenced by AI and reflect positively on the competitive position of the company.

Role of AI in cost reduction

Streamlining routine tasks, optimisation, and decreasing safety incidents can be some benefits for mining companies due to the integration of AI in the mining process (Hyder et al., 2019). Automation can reduce human intervention in routine operations which decreases the chances of manual error and decreases labour costs, whereas predictive maintenance reduces downtime and repair costs leveraging on algorithms to identify potential failures of equipment. For example, CITIC Telecom (2024), mentioned that Zijin Mining has invested in digital transformation and integrated AI in its operations such as using digital modelling combining geological and lab data to create 3D models to enhance the accuracy of mine sites. This helps to enhance operational efficiency due to the effective allocation of resources. Here, the digital transformation of mining operations in Zijin can be identified as a tool of competitiveness while setting a benchmark in the industry for operations. Here, advanced technologies such as AI-driven robots, or mineral processing factories helped the mining companies to control the cost of production which is instrumental for reinvesting in innovation to expand their mining capabilities and gain a competitive edge in the market. However, as the Chinese mining industry still going through digital transformation, the empirical evidence establishing the relationship between reduced costs and competitiveness is lacking. Hence, the second hypothesis has been generated.

H2a: Reduced costs mediate the relationship between AI and competitiveness.

Role of AI in safety improvements

Safety is a primary concern in the mining industry concerning the risks associated with the operations. According to Sadeghi et al. (2022), the mining industry is exposed to safety issues such as ground instability, toxic gases, and exposure to extreme temperatures. In this context, chemical hazards, and equipment and machinery accidents are also concerns which risk the worker's lives working in this industry. According to UNDRR (2023), despite employing 1% of the global workforce, mining fatalities account for 8% globally. For example, mining fatalities increased to 21.8% in 2021 in the US (US BLS, 2023). Similarly, the accidents and fatalities in coal mines in China recorded staggering statistics of 245 deaths in 168 accidents (Zhu et al., 2024). Consequently, safety in mining operations is a concern which AI can address. AI can be the catalyst for enhancing safety in mining operations due to automation, real-time monitoring, and predictive maintenance (Hyder et al., 2019). Here, AI-driven systems can evaluate mine conditions to identify the early signs of potential collapse and also guard the mine site. For example, Laizhou adopted cutting-edge automation to address safety risks in gold mining (Shen, 2023). AI-powered systems can analyse data from seismic sensors to predict structural instability, allowing operators to take preventive measures. Here, AI can help manage safety in mining and reduce accidents, enhancing the company's strategic position as a safe employer and gaining a competitive edge. However, there can be some challenges for companies in emerging economies such as China to understand the geographical context which are underexplored and hence created the context of the next hypothesis.

H2b: Improved safety mediates the relationship between AI and competitiveness.

Role of AI in innovation

Concerning the high competition in the mining sector, innovation is the catalyst for the mining industry to maintain competitiveness by leveraging advanced technologies that can revamp processes or business models. Corrigan and Ikonnikova (2024), opined that AI can enable companies to innovate by fostering technologies that can enhance traditional business models by integrating advanced techniques. For instance, geological modelling enabled by AI improves the process of exploration by accurately identifying high-value deposits which can reduce the time and cost of traditional mining methods (Mining World, 2024). Consequently, AI algorithms can help mining companies to optimise mining techniques which allows companies to extract resources efficiently. However, despite the discussion of the role of AI in enhancing innovation in literature, there is a gap in discussing the challenges of AI adoption, and also due to geographical bias most of the studies are focused on technology innovation in developed countries. These gaps in the existing literature create the need for contextual studies that define the net hypothesis.

H2c: Innovation mediates the relationship between AI and competitiveness.

Role of AI in sustainability

Given the increasing environmental concerns and regulatory pressure, Sustainability becomes is critical priority for the mining industry. Globally, the mining industry is responsible for 4 to 7% of the GHG emissions (Delevingne et al., 2020). Consequently, with 176.4 million metric tonnes of emissions, China Shenhua Energy is the company that has the highest carbon footprint in 2022 (Tiseo, 2023). This means that mining companies in China are susceptible to ecological impact which includes resource depletion, emission, and waste generation. However, the Chinese government is promoting green mine construction, and almost 1254 mining companies have been listed as green mine companies (Global Affairs Canada, 2022). In this context, given the pressure of regulatory shifts, the mining companies need to develop sustainability parameters to maintain a competitive edge. Alijoyo (2024) asserts that real-time data and monitoring supported by AI algorithms can help to optimise equipment settings which can reduce energy consumption effectively. Similarly, the predictive analysis in AI can optimise resource extraction and waste generation which can minimise the ecological impact of the mining (Liang et al., 2024). For example, a Chinese coal mine namely Mataihao Mine effectively decreased energy consumption due to the implementation of AI-powered systems which not only reduced costs but also decreased the ecological prints of the company (IEA, 2024). It means that a system can help to achieve sustainability goals by optimising energy consumption and reducing emissions and waste generation. However, the energy consumption of AI systems for large-scale data processing can offset the environmental impact. It means that the impact of AI on sustainability may be debatable which creates the hypothesis for this paper.

H2d: Sustainability mediates the relationship between AI and competitiveness.

Impact of firm size on the adoption of AI in the mining industry

Firm size can impact the adoption of AI-powered technologies in mining operations. According to Kutnjak (2021), the digital transformation of mining operations can be costly because the challenges such as infrastructure limitations, low investment in IT, and many more. Here, companies must have strong financial background for AI implementation which can be a constraint for small mining companies. Castillo-Vergara et al. (2024), mentioned that larger forms may have more chances to realise the opportunity of AI due to the sufficiency of resources whereas, smaller firms may lack resources to create infrastructure or technical expertise to adopt AI. However, concerning the agility and flexibility of smaller firms, these firms may adopt and integrate AI solutions tailored to their specific needs. Contrarily, the bureaucracy and hierarchical structure of large firms can delay decision-making and thus impact the firm’s ability to adopt and implement AI systems to realise its potential benefits. Here, the adoption of AI at scale requires overcoming resistance to change within entrenched operational systems and workforce practices, which can be a significant barrier for larger firms due to the large workforce comparatively. It means that the impact of firm size on AI adoption can be critical which may reshape the operational efficiency of the company. Here, the next hypothesis has been generated.

H3: Firm size moderates the relationship between AI and operational efficiency.

Theoretical model

The theoretical model for this study is the Technology-Organisation-Environment (TOE framework, which can help to understand the adoption of AI for mining companies. The TOE framework was developed by Tornatzky and Fleisher which created a structured approach to understand the factors of adoption and integration of technical innovation in the companies (Chiniah et al., 2019). The technological factor in the TOE framework comprises technical complexity and perceived benefits of the technical innovation which are analysed through organisational factors namely size, resources, and many more and environmental factors such as regulatory, legal, and social factors. This framework comprises that combined these factors impact the level and willingness of the adoption of technical innovation in the companies. Here, the high perceived benefits of technical innovation can enhance the willingness of the firms to adopt the technology which means that high ROI can convince the firm to adopt innovative technologies.

Chiniah et al. (2019), also state that organisational factors such as size, resources, and leadership are some critical factors which can impact the level of adoption of technical innovation in firms. For example, the integration of AI depends on the availability of financial and technical resources as the digital transformation of the firms requires significant investments. Here, the element in the TOE framework is the Environment which comprises external environment factors such as competition, regulation, and consumer demand. It means that firms adopt technical innovation due to the pressure of the external environment. For example, increasing awareness of sustainability issues compelled the firms to use advanced techniques to decrease the ecological impact. It can also help the companies to gain a competitive edge in the company. Therefore, the TOE Framework is particularly relevant for analyzing the adoption of AI in the mining sector because it captures the interplay of technological advancements, organizational capabilities, and environmental demands.

Research gaps

Although there are significant studies available demonstrating the transformative potential of AI, there is a substantial gap in understanding the impact and adoption of AI in the mining industry in China which may be a catalyst for its competitiveness. Also, due to the vast adoption of technological innovation in developed countries, there is limited research in the Chinese mining industry which is leading globally and hence creates a significant ground for research. In this context, unique technological, organizational, and environmental factors may impact the adoption and implementation of AI in Chinese companies which may impact the operational efficiency and competitiveness of the mining industry in China.

RESEARCH METHODOLOGY

This study explored the role of AI in enhancing competitiveness in the mining industry concerning the related factors of operational efficiency and firm size. In this paper, for the research methodology, the quantitative research approach was adopted with a cross-sectional research design for data collection at a single point in time. According to Taherdoost (2022), the quantitative method of research is appropriate to investigate causal relations between variables. Consequently, the chosen research method is suitable for this paper to identify the immediate relationship between constructs. The data for this paper is collected through a structured questionnaire based on the constructs adapted from existing literature in the specific relevance to the study.

A cross-sectional survey design was adopted to collect data from the employees in mining companies in China. According to Surucu and Maslakci (2020), in quantitative research design, the validity and reliability of results depend on data collection and analysis methods. In this context, the approach of a cross-sectional survey in undertaken research is suitable as it helped to collect effective data to assess the impact of AI-powered technologies such as predictive maintenance, automation, and real-time monitoring on operational efficiency and competitiveness. The key construct in this study namely AI adoption, operational efficiency factors such as cost reduction, safety, innovation, sustainability, competitiveness, and firm size were taken using scales in prior studies. Here, these factors are also grounded in the TOE framework which creates means to analyse the AI adoption in mining firms in China comprehensively.

Based on the key constructs, the questionnaire is divided into several parts which are taken from existing literature. For example, the constructs related to the adoption of AI such as predictive maintenance, automation, and real-time monitoring, adapted from Haleem et al. (2021) and Liang et al. (2024). Similarly, the dimension of operational efficiency has been taken from Hyder et al. (2019) and Liang et al. (2024). Also, the competitiveness focused on market leadership, profitability, and sustainability has been developed by Hossain et al. (2024) and Liang et al. (2024). Whereas, the firm size factors have been adapted from Castillo-Vergara et al. (2024). The developed close-ended questionnaire was measured using a five-point Likert scale which ranged from 1 (strongly disagree) to 5 (strongly agree).

Constructs	Questions	Source
Reduced Cost	AI-driven technologies reduced operational costs in my mining operations.	(Hyder et al., 2019)
Workplace Safety	The adoption of AI technologies improved workplace safety in mining operations.	(Hyder et al., 2019)
Innovation	AI has encouraged innovation in my company's mining processes.	Self-Developed based on (Corrigan & Ikonnikova, 2024)
Sustainability	AI has positively contributed to achieving sustainability goals by reducing environmental impact in mining operations.	(Liang et al., 2024)
Predictive Maintainance	AI-enabled predictive maintenance reduced equipment downtime in mining operations.	Self-Developed based on (Arinze et al., 2024)
	How often are AI-driven predictive maintenance tools used in your company?	Self-Developed based on (Arinze et al., 2024)
Automation	AI-enabled automation improved the efficiency of your mining operations.	(Haleem et al., 2021)

Real-time Monitoring	Is real-time monitoring effective in optimizing your operational decisions?	Self-Developed based on (Badmus et al., 2024)
Market leadership	AI helped your company achieve or maintain market leadership in the mining sector.	Self-Developed based on (Hossain et al., 2024)
Profitability	AI-driven operational efficiency improved your company's profitability.	Self-Developed based on (Hossain et al., 2024)
Sustainability	AI adoption supports long-term sustainability in terms of environmental and operational practices.	(Liang et al., 2024)
Firm Size	The size of my company influences the benefits gained from AI adoption.	Self-Developed based on (Castillo-Vergara et al., 2024)

To ensure that the surveyed participants are familiar with AI-driven technologies in mining operations, a purposive sampling have been done which generated 150 valid responses from engineers, managers, and technicians across various mining firms in China. The online data collection have been conducted using social media sites to join mining professional groups to forward the questionnaire. Ethical considerations were strictly observed as participants were duly informed about the purpose of the study and their rights to anonymity and confidentiality. Furthermore, the data analysis was performed with SPSS software. The SPSS software provides a comprehensive data analysis package for quantitative data analysis (Rahman & Muktadir, 2021). In this software package, Descriptive Statistics, Exploratory Factor Analysis, Reliability Testing, Correlation Analysis, Multiple regression Analysis, and Goodness-of-Fit Testing are included. Altogether these analytical models conform to the validity of the research. For example, Internal consistency can be evaluated using Cronbach's alpha, with a threshold of 0.7 indicating acceptable reliability (Taber, 2018). Similarly, the explanatory power of the model was assessed using the R-squared value, with a focus on p-values below 0.05 for statistical significance. Here, Correlation analysis defines the relationship between independent and dependent variables, while, regression analysis ensures the reliability of the tests by identifying the hypotheses. Thus, The methodological approach employed in this study ensures the reliability and validity of the findings.

RESULT

Descriptive statistics

Table 2: Descriptive statistics

Category	**N**	**%**
Age		
31–50	67	44.67%
55 and above	28	18.67%
Above 50	21	14.00%
Under 18	34	22.67%
What is your role in the organisation?		
Engineer	5	3.33%
Manager	53	35.33%
Researcher	34	22.67%
Technician	58	38.67%
How many years have you worked in the mining sector?		
1–5 years, 5–10 years	78	52.00%
Less than 1 year	35	23.33%
More than 10 years	37	24.67%

What type of mining is your organisation primarily involved in?		
Coal	40	26.67%
Lithium	35	23.33%
Other	8	5.33%
Rare Earths	67	44.67%

Table 1 represents the distribution of various demographic categories within the sample. The results reveal that the majority of the participants are between the ages of 31 and 50 (44.67%), followed by those under the age of 18, 22.67%, 55 and over (18.67%), and above 50 (14.00%). The largest category in terms of roles inside the organization is technicians (38.67%), who are followed by engineers (3.33%), managers (35.33%), and researchers (22.67%). The majority of respondents (52.0%) have 1–10 years of experience in the mining industry, while fewer have less than 1 year (23.33%) or more than 10 years (24.67%). 44.67% of respondents said that rare earths were their top priority when it came to mining types, followed by coal (26.67%), lithium (23.33%), and other types (5.33%). These results demonstrate a varied profile of respondents, with a notable proportion of technical and managerial positions, a focus on rare earth mining, and substantial representation from seasoned professionals.

Construct reliability and validity

Table 3: Reliability

	Cronbach's alpha
Operational Efficiency	0.888
Artificial Intelligence	0.773
Competitiveness	0.765

The reliability of the scales employed in this study is shown by Cronbach's alpha values in Table 3. Cronbach's alpha for the Operational Efficiency scale is 0.888, which indicates that the items are very reliable and have excellent internal consistency. Similar to this, the Artificial Intelligence scale shows strong reliability with a Cronbach's alpha of 0.773, indicating that the items are well-correlated and accurately assess the intended construct. A Cronbach's alpha of 0.765 indicates adequate internal consistency for analysis, indicating acceptable reliability for the Competitiveness scale as well. All things considered, these results attest to the validity and suitability of the measurement instruments employed for the constructs for statistical analysis.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.902
Bartlett's Test of Sphericity	Approx. Chi-Square	1094.067
	df	66
	Sig.	.000

The above table confirms that the data is suitable for factor analysis by Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy. The data is well-suited for factor analysis, as indicated by the "marvelous" KMO value of 0.902, which indicates outstanding sample adequacy. The correlation matrix is not an identity matrix, as shown by the significant results of Bartlett's Test of Sphericity (Approx. Chi-Square = 1094.067, df = 66, p = 0.001). It would appear from this that there is enough correlation between the variables to find important factors. In general, these findings offer compelling evidence for moving further with factor analysis.

Multiple linear regression

Table 4: Regression analysis

Coefficients[a]						
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.553	.180		3.068	.003
	Artificial Intelligence	.750	.071	.654	10.521	.000

a. a. Dependent Variable: Competitiveness
b. R-Squared: 0.428
c. F: 110.690
Sig: <0.001

According to the statistical findings in Table 4, Hypothesis H1, which asserts that "Artificial Intelligence (AI) positively influences Competitiveness in the mining sector," is supported. According to the Model Summary, AI has a significant impact and accounts for 42.8% of the variance in competitivenes. AI substantially predicts competitiveness, according to the ANOVA table, which also demonstrates that the regression model is statistically significant ($F(1, 148) = 110.690$, $p < 0.001$). A positive and substantial association can be shown in the Coefficients table ($\beta = 0.654$, $t = 10.521$, $p < 0.001$). According to the unstandardized coefficient ($B = 0.750$), competitiveness rises by 0.750 for every unit increase in AI usage.

Mediation analysis

Table 5: Mediation Effect I

Model	**4**
Dependent Variable (Y)	Competitiveness (Comp)
Independent Variable (X)	Artificial Intelligence (AI)
Mediator (M)	Reduced Costs (Redu)
Sample Size (N)	150
Outcome Variable	Competitiveness (Comp)
Model Summary for Mediator (Redu)	$R^2 = 0.3597$, $F(1, 148) = 83.1526$, $p < 0.001$
Model Summary for Outcome (Comp)	$R^2 = 0.5586$, $F(2, 147) = 93.0092$, $p < 0.001$
Path Coefficients (X → M)	Coeff = 0.6961, SE = 0.0763, t = 9.1188, p < 0.001, 95% CI [0.5452, 0.8469]
Path Coefficients (M → Y)	Coeff = 0.4464, SE = 0.0677, t = 6.5973, p < 0.001, 95% CI [0.3127, 0.5802]
Direct Effect (X → Y)	Coeff = 0.4394, SE = 0.0785, t = 5.5948, p < 0.001, 95% CI [0.2842, 0.5946]
Indirect Effect (X → M → Y)	Effect = 0.3108, BootSE = 0.0631, BootLLCI = 0.1959, BootULCI = 0.4407

The results in Table 5 indicate that "Reduced Costs mediate the relationship between Artificial Intelligence (AI) and Competitiveness," as proposed by Hypothesis H2a. In addition to the direct impact of AI on competitiveness ($B = 0.4394$, $p < 0.001$), the indirect impact through lower costs is also noteworthy (Effect = 0.3108, BootLLCI = 0.1939, BootULCI = 0.4409). According to this, AI has a beneficial effect on reduced costs ($B = 0.6961$, $p < 0.001$), which dramatically raises competitiveness ($B = 0.4464$, $p < 0.001$). The partial mediation emphasizes how cost reduction is essential in tying the adoption of AI to competitiveness.

Table 6: Mediation effect II

Model	**4**
Dependent Variable (Y)	Competitiveness (Comp)
Independent Variable (X)	Artificial Intelligence (AI)
Mediator (M)	Improved Safety (ImpS)
Sample Size (N)	150
Outcome Variable	Competitiveness (Comp)
Model Summary for Mediator (ImpS)	$R^2 = 0.4286$, $F(1, 148) = 111.0000$, $p < 0.001$
Model Summary for Outcome (Comp)	$R^2 = 0.5190$, $F(2, 147) = 79.2931$, $p < 0.001$
Path Coefficients (X → M)	Coeff = 0.8167, SE = 0.0775, t = 10.5357, p < 0.001, 95% CI [0.6635, 0.9698]
Path Coefficients (M → Y)	Coeff = 0.3670, SE = 0.0696, t = 5.2754, p < 0.001, 95% CI [0.2295, 0.5045]

Direct Effect (X → Y)	Coeff = 0.4504, SE = 0.0868, t = 5.1904, p < 0.001, 95% CI [0.2789, 0.6219]
Indirect Effect (X → M → Y)	Effect = 0.2997, BootSE = 0.0618, BootLLCI = 0.1828, BootULCI = 0.4260

Table 6 shows that, Hypothesis H2b, which holds that "Improved Safety mediates the relationship between Artificial Intelligence (AI) and Competitiveness," is highly supported. According to the first model, AI has a substantial impact on Improved Safety (B = 0.8167, $p < 0.001$). According to the second model, increased safety also considerably increases competitiveness (B = 0.3670, $p < 0.001$). In addition to the direct impact of AI on competitiveness (B = 0.4504, $p < 0.001$), the indirect impact through enhanced safety is also noteworthy (Effect = 0.2997, BootLLCI = 0.1828, BootULCI = 0.4260). This highlights the crucial significance of improved safety by showing that it partially mediates the link.

Table 7: Mediation effect III

Model	**4**
Dependent Variable (Y)	Competitiveness (Comp)
Independent Variable (X)	Artificial Intelligence (AI)
Mediator (M)	Innovation (Inno)
Sample Size (N)	150
Outcome Variable	Competitiveness (Comp)
Model Summary for Mediator (Inno)	R^2 = 0.4715, F(1, 148) = 132.0194, p < 0.001
Model Summary for Outcome (Comp)	R^2 = 0.5569, F(2, 147) = 92.3816, p < 0.001
Path Coefficients (X → M)	Coeff = 0.8216, SE = 0.0715, t = 11.4900, p < 0.001, 95% CI [0.6803, 0.9629]
Path Coefficients (M → Y)	Coeff = 0.4735, SE = 0.0724, t = 6.5427, p < 0.001, 95% CI [0.3305, 0.6166]
Direct Effect (X → Y)	Coeff = 0.3611, SE = 0.0866, t = 4.1695, p < 0.001, 95% CI [0.1899, 0.5322]
Indirect Effect (X → M → Y)	Effect = 0.3891, BootSE = 0.0670, BootLLCI = 0.2633, BootULCI = 0.5246

Table 7 shows that, Hypothesis H2c, which holds that "Innovation mediates the relationship between Artificial Intelligence (AI) and Competitiveness," is highly supported. The first model shows a significant influence of AI on innovation (B = 0.8216, $p < 0.001$). In the second model, competitiveness is significantly improved by innovation (B = 0.4735, $p < 0.001$). While the indirect effect through innovation is also substantial (Effect = 0.3891, BootLLCI = 0.2655, BootULCI = 0.5291), the direct effect of AI on competitiveness is still considerable (B = 0.3611, $p < 0.001$). This suggests partial mediation, underscoring the crucial part innovation plays in boosting competitiveness with AI.

Table 8: Mediation effect IV

Model	**4**
Dependent Variable (Y)	Competitiveness (Comp)
Independent Variable (X)	Artificial Intelligence (AI)
Mediator (M)	Sustainability (Sust)
Sample Size (N)	150
Outcome Variable	Competitiveness (Comp)
Model Summary for Mediator (Sust)	R^2 = 0.3600, F(1, 148) = 83.2587, p < 0.001
Model Summary for Outcome (Comp)	R^2 = 0.4942, F(2, 147) = 71.8286, p < 0.001
Path Coefficients (X → M)	Coeff = 0.9173, SE = 0.1005, t = 9.1246, p < 0.001, 95% CI [0.7186, 1.1159]
Path Coefficients (M → Y)	Coeff = 0.2416, SE = 0.0550, t = 4.3919, p < 0.001, 95% CI [0.1329, 0.3503]

Direct Effect (X → Y)	Coeff = 0.5286, SE = 0.0841, t = 6.2862, p < 0.001, 95% CI [0.3624, 0.6947]
Indirect Effect (X → M → Y)	Effect = 0.2216, BootSE = 0.0571, BootLLCI = 0.1043, BootULCI = 0.3290

Table 8 shows that, Hypothesis H2d, which holds that "Sustainability mediates the relationship between Artificial Intelligence (AI) and Competitiveness," is highly supported. The first model indicates that AI has a considerable impact on sustainability (B = 0.9173, $p < 0.001$). In turn, competitiveness is greatly improved by sustainability (B = 0.2416, $p < 0.001$) in the second model. While the indirect impact through sustainability is also substantial (Effect = 0.2216, BootLLCI = 0.1043, BootULCI = 0.3290), the direct impact of AI on competitiveness is still significant (B = 0.5286, $p < 0.001$). This suggests partial mediation, highlighting how sustainability is crucial in tying AI adoption to competitiveness.

Table 9: Moderation effect I

Model	**1**
Dependent Variable (Y)	Operational Efficiency (OpperE)
Independent Variable (X)	Artificial Intelligence (AI)
Moderator (W)	Firm Size (FirmS)
Sample Size (N)	150
Model Summary for Outcome (OpperE)	R^2 = 0.6107, F(3, 146) = 76.3474, p < 0.001
Path Coefficients (X → Y)	Coeff = 0.2126, SE = 0.1451, t = 1.4659, p = 0.1448, 95% CI [-0.0740, 0.4993]
Path Coefficients (W → Y)	Coeff = -0.1516, SE = 0.0923, t = -1.6420, p = 0.1028, 95% CI [-0.3341, 0.0309]
Interaction Effect (X × W → Y)	Coeff = 0.1530, SE = 0.0392, t = 3.8998, p < 0.001, 95% CI [0.0755, 0.2306]
Change in R^2 (Interaction)	ΔR^2 = 0.0406, F(1, 146) = 15.2088, p < 0.001
Conditional Effects of X on Y (at values of W)	
Firm Size = 1.0000	Effect = 0.3657, SE = 0.1106, t = 3.3078, p = 0.0012, 95% CI [0.1472, 0.5842]
Firm Size = 2.0000	Effect = 0.5187, SE = 0.0805, t = 6.4432, p < 0.001, 95% CI [0.3596, 0.6778]
Firm Size = 5.0000	Effect = 0.9778, SE = 0.0880, t = 11.1144, p < 0.001, 95% CI [0.8040, 1.1517]

Table 9 shows that, firm size moderates the association between AI adoption and operational efficiency, according to the statistically significant interaction term (AI × Firm Size) (B = 0.1530, $p < 0.001$). The conditional effects demonstrate that AI's impact on operational efficiency intensifies with business size. The effect of AI is moderate at low firm sizes (FirmS = 1) (B = 0.3657), but it becomes stronger at larger company sizes (B = 0.9778 at FirmS = 5), indicating the moderating effect of firm size.

Table 10: Final summary

Hypothesis	**Statement**	**Decision**
H1	AI positively influences Competitiveness in the mining sector.	Supported
H2a	Reduced Costs mediate the relationship between AI and Competitiveness.	Supported
H2b	Improved Safety mediates the relationship between AI and Competitiveness.	Supported
H2c	Innovation mediates the relationship between AI and Competitiveness.	Supported
H2d	Sustainability mediates the relationship between AI and Competitiveness.	Supported
H3	Firm Size moderates the relationship between AI and Operational Efficiency.	Supported

DISCUSSION

The research findings effectively conform to the transformative potential of AI-driven technologies on the competitiveness of the mining industry in China. The results imply that AI-powered techniques such as automation, predictive maintenance and real-time monitoring reflect positively on the operational efficiency of the mining operations concerning specific factors such as cost, safety, innovation and sustainability which enhance the competitiveness of the companies working in the mining industry in China.

The results exacerbated the positive impact of AI-driven technologies on the competitiveness of the mining industry in China which supports hypothesis 1. Aligned with the findings of Balcıoğlu et al. (2024) this research reinforced the potential of AI in enhancing the competitive advantage of mining companies by improving safety and sustainability. Consequently, predictive maintenance, automation, and real-time monitoring are some AI-powered technologies that help to enhance the profitability and market leadership of mining companies due to their competitive edge in the market. In the specific context of China, these findings underpin that the benefits of AI implementation outweigh the challenges and costs of implementation.

The results also supported hypothesis 2 which means that this study confirms that AI-powered technology drives the operational efficiency in mining companies which perpetuates the competitive edge in the company. It means that the analysis illustrated the positive impact of AI on the undertaken elements of operational efficiency such as cost reduction, safety, innovation, and sustainability.

Confirmed by research results, this study reinforces the findings of work done by Hyder et al. (2019). Consequently, it confirms that AI-driven cost reduction in mining companies in China reflects positively on the competitiveness of the mining companies. For example, Automation and predictive maintenance can minimise operational inefficiencies by optimising resource allocation and eventually, with low-cost operations, mining companies can achieve cost leadership in the market. Although the smaller forms in the mining industry may have to face the challenges of AI implementation due to resource constraints, the mining companies need huge capital to establish, which means that the proportion of smaller companies can be low, Here, the smaller companies can realise the advantages of AI by implementing for specific niche purpose rather than transforming all the operations digitally.

The research results also validated the hypothesis that conveys the positive impact of AI-driven technologies on safety which reflects positively on competitiveness. These result findings support the findings of prior research conducted by Hyder et al. (2019), which emphasised that enhanced safety can not only reduce operational downtime but also can enhance employee dissatisfaction positively. For example, real-time monitoring can be used for hazard detection technologies which is crucial to create a safe work environment by reducing workplace accidents. Here, this technology is particularly significant for the accident-prone business such as mining. In this context, the reduced statistics of accidents and fatalities can enhance the market reputation of the business and create a competitive advantage for the company.

Similarly, the research results confirm the positive impact of AI on innovation which is a crucial element for companies to maintain their competitiveness. According to Liang et al. (2024), the changing market factors such as increasing awareness for sustainability and regulatory pressure for green mines create the need for companies to innovate. Here, innovation can be the factor which can help to create differentiation and enhance the competitiveness of the mining operations as described by Alijoyo (2024), that AI can be instrumental for companies to implement technological and process innovation. This means that AI can create a strategic advantage for mining companies to create differentiation and reinforce competitive advantage in the market.

This study also revealed that sustainability is a mediating factor between AI and competitiveness which means that AI-driven technologies such as real-time monitoring, and energy optimisation can help the mining companies to reduce ecological footprints. This is crucial for companies concerning the stakeholder's expectations and regulatory pressure. These findings reinforce the findings of Liang et al. (2024). In the context of China which means that AI-driven technology is the reason for the competitiveness in the mining industry in China mediated by sustainability.

Collectively, it can be said that cost reduction, safety, innovation, and sustainability are the elements of operational efficiency that create a comprehensive mediating framework for understanding the impact of AI on competitiveness. These dimensions highlight the multifaceted ways in which operational efficiency contributes to market leadership and profitability of the mining companies in China.

The research findings also supported the hypothesis that firm size can impact the relationship between AI and operational efficiency which critically reflects on the competitiveness too. According to Castillo-Vergara et al. (2024), larger firms have huge resources that can help to implement AI technology to transform operations. Here, the economies of scale, established infrastructure, and extensive resources can help large firms to integrate AI into their operations effectively, while, smaller firms may have to face resource constraints. However, by leveraging agility and innovative ideas, the smaller firms can adopt AI for niche solutions in the mining process which can help to enhance some aspects of operations and create a competitive edge for the companies. Thus, it can be said that the adoption of AI can enhance the competitiveness of the mining industry in China.

CONCLUSION

This study investigated the role of AI in improving the competitiveness in the mining industry in China. In this context, the findings revealed the intricate relationship between AI and the mining firms' operational efficiency, which reflects positively on the company's competitiveness. The findings demonstrated that AI enhances the operational efficiency of the mining forms with cost reduction, enhancing safety, innovation, and sustainability which create a differentiation in the market and thereby positively improve the competitiveness of the company. However, firm size has been concluded as a moderating factor as large firms have more resources to integrate AI into their operations. Here, the innovative approach and agility of smaller mining companies can help to integrate the AI in niche production process which is contingent on high competitiveness.

Based on the TOE framework, this paper created multiple theoretical implications for mining companies considering the insights into the interplay of technological, organisational and environmental factors in AI adoption in mining firms. This paper validates all these three factors in the TOE framework and advances the theory with the integration of operational efficiency as a mediator. It means that the multidimensional nature of operational efficiency can be a driving force for the competitiveness of the mining firms. This study also extends the TOE framework by connecting the firm size as a moderating factor which creates new insights into the impact of organisational factors on the results of technological changes in the company.

Moreover, based on the research findings, the practical implications have also been drawn which creates recommendations for mining companies, policymakers, and technology providers in China. Concerning the positive impact of AI on competitiveness, the mining forms are recommended to prioritise AI investments to transform the company digitally. This means that forms should prioritise investment in AI-driven techniques such as predictive maintenance and real-time monitoring to enhance their competitiveness. Here, the large firms need to address the challenge of bureaucracy and provide training to employees to foster a culture of innovation, whereas, smaller firms should focus on targeted high-impact AI solutions. Similarly, the policymakers are recommended to provide financial help such as grants and subsidies to smaller firms to support AI adoption for smaller firms. Also, the regulatory forces should be encouraging firms to adopt sustainable mining practices by promoting the use of AI solutions for positive ecological impact. Also, the technological providers should focus on creating AI solutions to cater for the diverse needs of small and large firms to create long-term relations with the firms.

Even though this study highlights the positive impact of AI on the competitiveness of mining companies, it also acknowledges its limitations such as cross-sectional design and focus on the Chinese mining industry may restrict the generalizability of the research findings. However, future studies can address these limitations through longitudinal studies and comparative analysis. On the whole, this study confirms that AI positively impacts the competitiveness of Chinese mining firms.

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APPENDIX

Case Processing Summary

		N	%
Cases	Valid	150	100.0
	Excluded[a]	0	.0
	Total	150	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.888	4

Case Processing Summary

		N	%
Cases	Valid	150	100.0
	Excluded[a]	0	.0
	Total	150	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.773	4

Case Processing Summary

		N	%
Cases	Valid	150	100.0
	Excluded[a]	0	.0
	Total	150	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.765	3

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.902
Bartlett's Test of Sphericity	Approx. Chi-Square	1094.067
	df	66
	Sig.	<.001

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.654[a]	.428	.424	.9401820560

a. Predictors: (Constant), Artificial Intelligence

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	97.843	1	97.843	110.690	<.001[b]
	Residual	130.823	148	.884		
	Total	228.667	149			

a. Dependent Variable: Comp

b. Predictors: (Constant), Artificial Intelligence

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.553	.180		3.068	.003
	Artificial Intelligence	.750	.071	.654	10.521	<.001

a. Dependent Variable: Comp

```
Model  : 4
    Y  : Comp
    X  : AI
    M  : Redu

Sample
Size:  150

**************************************************************************
OUTCOME VARIABLE:
 Redu

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5998      .3597     1.0132    83.1526     1.0000   148.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .4828      .1928     2.5040      .0134      .1018      .8638
AI            .6961      .0763     9.1188      .0000      .5452      .8469

**************************************************************************
OUTCOME VARIABLE:
 Comp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7474      .5586      .6866    93.0092     2.0000   147.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .3370      .1621     2.0798      .0393      .0168      .6573
AI            .4394      .0785     5.5948      .0000      .2842      .5946
Redu          .4464      .0677     6.5973      .0000      .3127      .5802
```

```
Model  : 4
    Y  : Comp
    X  : AI
    M  : ImpS

Sample
Size:  150

**************************************************************************
OUTCOME VARIABLE:
 ImpS

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6547      .4286     1.0448   111.0000     1.0000   148.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .2606      .1958     1.3308      .1853     -.1263      .6475
AI            .8167      .0775    10.5357      .0000      .6635      .9698

**************************************************************************
OUTCOME VARIABLE:
 Comp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7204      .5190      .7483    79.2931     2.0000   147.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .4570      .1667     2.7414      .0069      .1275      .7864
AI            .4504      .0868     5.1904      .0000      .2789      .6219
ImpS          .3670      .0696     5.2754      .0000      .2295      .5045
```

```
Model  : 4
    Y  : Comp
    X  : AI
    M  : Inno

Sample
Size:  150

**************************************************************************
OUTCOME VARIABLE:
 Inno

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6866      .4715      .8890   132.0194     1.0000   148.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .1027      .1806      .5686      .5705     -.2542      .4596
AI            .8216      .0715    11.4900      .0000      .6803      .9629

**************************************************************************
OUTCOME VARIABLE:
 Comp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7463      .5569      .6892    92.3816     2.0000   147.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .5040      .1592     3.1655      .0019      .1893      .8186
AI            .3611      .0866     4.1695      .0001      .1899      .5322
```

```
Model  : 4
    Y  : Comp
    X  : AI
    M  : Sust

Sample
Size:  150

**************************************************************************
OUTCOME VARIABLE:
 Sust

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6000      .3600     1.7572    83.2587     1.0000   148.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .3173      .2539     1.2497      .2134     -.1845      .8191
AI            .9173      .1005     9.1246      .0000      .7186     1.1159

**************************************************************************
OUTCOME VARIABLE:
 Comp

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7030      .4942      .7867    71.8286     2.0000   147.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .4759      .1708     2.7865      .0060      .1384      .8135
AI            .5286      .0841     6.2862      .0000      .3624      .6947
Sust          .2416      .0550     4.3919      .0000      .1329      .3503
```

```
    Y  : OpperE
    X  : AI
    W  : FirmS

Sample
Size:  150

**************************************************************************
OUTCOME VARIABLE:
 OpperE

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .7815      .6107      .5787    76.3474     3.0000   146.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     1.0619      .3102     3.4230      .0008      .4488     1.6750
AI            .2126      .1451     1.4659      .1448     -.0740      .4993
FirmS        -.1516      .0923    -1.6420      .1028     -.3341      .0309
Int_1         .1530      .0392     3.8998      .0001      .0755      .2306

Product terms key:
 Int_1    :        AI        x        FirmS

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0406    15.2088     1.0000   146.0000      .0001
----------
    Focal predict: AI        (X)
          Mod var: FirmS     (W)

Conditional effects of the focal predictor at values of the moderator(s):

      FirmS     Effect          se          t          p       LLCI       ULCI
```