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Research paper

An International Comparative Study on The Performance of Big Data Transformation in The Energy Industry: Empirical Analysis of Developing and Developed Economies

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Abstract

In the modern energy industry, the implementation of big-data technologies has taken the form of a strategic necessity, as the requirements of digital efficiency, environmental sustainability, and financial stability are being raised simultaneously. This paper is an empirical evaluation of the effects of big-data adoption on financial performance and risk mitigation at the firm level and focuses on publicly traded Chinese energy firms in 2015-2024. The aim is to measure the influence of the digital maturity in three levels of transformation: pre, transition, and mature, and compare these results against the known benchmarks of advanced economies. Using multi-method analytical framework, including panel regression, difference-in-differences (DiD) estimation, analysis of variance (ANOVA), and robustness testing using generalized method of moments (GMM) and quantile regression, the current study evaluates the following three outcomes: profitability (EBIT margin), financial stability (Altman Z-Score), and bankruptcy risk (Ohlson O-Score). The findings show that the performance of the corporation increases over the years: the EBIT margin increases by 2.48 percentage points and the Z-Score by 0.38 points, during the mature stage, and the O-Score decreases by 0.80 points. A sectoral analysis shows that electric power firms are the most responsive, with less-pronounced gains in coal firms. Together, the results provide substantial support that the big data transformation enhances operational efficiency and financial strength, and has ramifications on strategic investment, policy development, and digital modernization in the emerging and developed energy markets.

Keywords: *Big Data Transformation; Energy Sector; Financial Performance; Risk Management; Digitalization; China; Sectoral Comparison.*

1. Introduction

The global energy markets are undergoing a radical change that is driven by the ubiquitous climate demands, escalated volatility in the supply of resources, and the rapid changes in consumer demands. The reports of the International Energy Agency (IEA) (Zhou et al., 2016; Onyeji-Nwogu et al., 2020) note that the global energy demand will rise by more than 25 percent by 2040, with more than 70 percent of the anticipated growth concentrated in the emerging markets. Meanwhile, the biggest source of carbon emissions in the world is the energy sector, and it constitutes approximately 73.2 % of the total volume of greenhouse gas emissions in 2023. Such forces have made it necessary to decarbonize, diversify, and modernize global infrastructure. In this evolving nature, large variability of digital technologies, i.e., big data analytics, artificial intelligence (AI), and industrial Internet of Things (IIoT) is gaining momentum to support grid stability, resource efficiency, and minimize externalities such as the environment (Ko et al., 2017).

Although great progress has been achieved in the field of digital innovation, the development remains very heterogeneous when it comes to the implementation of the technology into the energy industry. Developed countries, especially the United States, Germany, and Japan, have managed to develop large-scale digital transformation programs in their utility and renewable energy sectors (Park 2022; Sarabdeen et al. 2024). On the other hand, developing countries have started to catch up significantly, driven by policy change and strengthened access to digital capital. The example of China is the implementation of the plan for the new infrastructure (2020), which is planned to invest over 10 trillion Chinese yuan (about 1.4 trillion USD) and develop digital growth in the energy, transport, and smart-city infrastructure. However, the economic consequences of such macro-level changes on the level of firm performance are poorly measured (Mushtaq & Qurat-ul-Ann, 2024; Hunt et al., 2024).

The proposed study will address an important empirical gap as it examines the effects of big-data-driven transformation on the financial performance and risk profile of companies in the energy sector in a developing economy. Even though the qualitative benefits of digitalization are widely testified by scholars and practitioners (e.g., process automation and demand forecasting), little quantitative evidence explains how such changes can be related to practical financial metrics like EBIT margin, Z-Score, and O-Score. Similarly, the current literature has been silent on the sector-based differences, specifically the lower level of adoption rates in coal firms relative to the increased rate of digitization in electric and diversified energy companies. The current paper rectifies these concerns by conducting a comparative time-series study of the Chinese energy companies in 2015-2024, with the help of a variety of empirical approaches (Lisin et al., 2022; Li et al., 2024).

The paper deals with a pressing worldwide need for the harmonization of technological innovation and financial robustness in one of the most capital-intensive and environmentally demanding industries, energy. Despite the potential of the digital transformation to bring long-term economic and ecological benefits, its actual value remains unequally spread among economies and industries (Li et al., 2022). It is also critical to determine which firms benefit the most, in what time and context, to ensure effective capital allocation, reduce transition risks, and speed up digital maturity. The proposed research, therefore, aims to provide an empirical connection between big data transformation and firm performance, thus filling an existing gap in knowledge and offering practical intelligence to stakeholders who must deal with the intricate environment of digital energy reform (Marinakis, 2020).

Digitalization has become a strategic requirement in the field of global energy transformation to raise the efficiency of operations, financial stability, and environmental compliance. On the other hand, one of the main gaps that exists is the lack of empirical evidence regarding the impact of the big data transformation on financial performance and risk at the firm level, especially in the developing and developed economies and different energy subsectors. This is especially relevant in terms of policy design and investment plan in countries like China, where energy companies face a two-fronted pressure of modernization and sustainability (Baidya et al., 2021; Liu et al., 2024). The paper presents a data-driven, systematic exploration of the impacts of the digital investment in the energy sector between 2015 and 2024. Based on financial scoring and panel econometric measures, the analysis evaluates the performance results of 58 firms, which gives empirical evidence on the value creation potential of digitalisation to both investors, corporate decision-makers, and policymakers. By incorporating the sectoral, temporal, and macroeconomic aspects, the research provides novel empirical evidence that explains the strategic consequences of digital investment in the energy sector (Munodawafa & Johl, 2019).

Considering the defined problem and hypotheses, this study aims to:

1) In this quantitative analysis of the impact of big data transformation on the financial performance of energy companies, the alteration in EBIT margin in the pre-transformation, transition, and maturity phases was calculated.
2) The effect of digitalization on the financial stability and risk exposure of the enterprise was assessed with the help of the Altman Z-Score and Ohlson O-Score diagnostic indicators.
3) There was a comparative study of the results of digital transformation between Chinese energy companies, which are in a developing economy, and companies in developed economies, considering contextual and policy-driven variables.
4) The performance of transformation within specific sectors was compared, especially coal, electric power, oil & gas, and diversified energy sectors, to determine the difference in responsiveness to digital adoption.
5) The interactive effect of sectoral factors, national economic conditions, and the timing of transformation was examined to determine their effect on the firm-level financial resilience and profitability.

These objectives collectively aim to capture the heterogeneity, causal mechanisms, and performance implications of big data-driven transformation within and across global energy industry contexts.

These objectives guide the empirical investigation into the value and variability of digital transformation across economic and industrial contexts.

To address the research objectives and bridge the identified empirical gaps, this study offers the following key contributions:

- The current study provides empirical data that big data transformation leads to an increase in EBIT margin at various stages of adoption.
- The given analysis measures the resulting change in corporate risk using the prism of the Z-Score and O-Score measures.
- A comparative look shows that the results of digitalization in Chinese and developed-economy companies are divergent, and also explains segmental differences: electric and diversified energy companies always achieve the highest increase.
- A combined model of sector and economy type and transformation timing is proposed, which serves as a scheme to explore the financial stability of firms in the face of digital transformation.

The paper consists of five major parts. In the Introduction, the research problem, objectives, and contextual background are outlined. The Literature Review brings together previous research on digital transformation and the performance of the energy sector. The Methodology also explains the sources of data, variables, and statistical models used. The Results and Discussion section contains the interpretation of empirical findings, comparisons, and analyses. The conclusion is the last section, which summarizes the main findings, mentions the limitations, and suggests future research directions.

2. Literature review

2.1. Big data transformation and digitalization in the energy sector

It is a well-known fact among researchers that big data has revolutionized the energy systems by implementing aspects like predictive maintenance, smart grid, and emissions prediction. The study (Marinakis, 2020) used sensor-based energy simulation methods to increase the energy efficiency of buildings and the grid management, which resulted in calculable enhancements in the distribution of loads and energy efficiency in consumption. Baidya (Baidya et al., 2021) conducted a systematic review of 96 peer-reviewed studies and highlighted such primary advantages as demand-side optimization, as well as the challenge of data interoperability and institutional resistance to change. Liu (Liu et al., 2024), based on the data of the Big Data Comprehensive Pilot Zone in China, Xu et al. (Xu et al., 2020) carried out an employed panel regression and concluded that the development of big data in China was associated with a decrease in carbon emissions by 6.8 %. The research was however, limited to samples of pilot regions, thus the external validity is limited. In comparison, Munodawafa and Johl (Munodawafa & Johl, 2019) used structural-equation modeling (SEM) to investigate the adoption of big data in a sample of the African Energy Firms and found a statistically significant relationship between analytics capabilities and eco-innovation, albeit with a limited data set (SMEs). Zhang et al. (Zhang et al., 2018) proposed a simulation-optimization model of energy-intensive manufacturers and verified the enhanced process efficiency, but the authors did not include the utility sectors..

(Muhammed & Tekbiyik-Ersoy2020) performed the comparative policy analysis of renewable energy development in China, the U.S., and Brazil. The analysis demonstrated that the Chinese approach to regulation based on the use of data had a significant positive impact on renewable investment, but in the United States, the increase was due to digital innovation in the private sector. (Li et al. 2022) conducted a descriptive trend analysis, according to which the pandemic caused a break in renewable energy financing in the developing economies, and the effects of the pandemic were especially harsh in the countries without digital resilience systems. (Ponnusamy et al. 2021) provided a bibliometric and thematic synthesis of 144 publications, where AI-enabled big-data platforms were identified as the basis of smart-grid modernization; nevertheless, there were not many empirical validations. Altman (Altman et al., 2017) carried out a survey of the international applications of Z-score with an emphasis on their ability to determine the impact of technological change on financial health. (Ma and Li 2023) utilized the modeling of environmental Kuznets curves across a Chinese panel to reveal a rising and subsequent decline in energy intensity relative to digitalization, but causality was not separated. (Shaaban-Nejad and Shirazi 2022) used regression analysis to estimate ICT adoption between countries and found that there is a high correlation between digital infrastructure and environmental performance in OECD countries, but not at the industry level. Taken together, those studies support the transformative power of big data in energy systems, but they also emphasize the need to conduct more sector- and cross-economy empirical assessments.

2.2. Financial performance and risk management in sectoral contexts

The studies have increased the pressure on the scale to which the digital transformation influences the risk mitigation and the financial performance in the energy market. Ren et al. (2023) used panel regression on a sample of renewable energy companies headquartered in China and determined that digital transformation had a significant positive impact on the return on assets (ROA) and EBIT margins, but the effect became significant after 2015, although the results were limited to the firms located in the specified policy areas. In comparison, Moktadir et al. 2019) have used a case-based multi-criteria decision-making approach and found that the existence of financial, infrastructural, and talent-based barriers prevented the complete exploitation of big data benefits in the manufacturing supply chains of developing economies. In the literature on growth accounting, decomposition methods have been used to question the productivity gains due to ICT in terms of country groups and showed that productivity gains were large both in developed and emerging economies, but institutional weaknesses limited more stable results in developing countries. In a different publication, Ansari et al. (Ansari et al., 2020) trained a neural network and created a hybrid metaheuristic-trained neural net to predict bankruptcy, and they found that companies using AI-based financial forecasting improved risk-scoring performance, especially when Ohlson O-Score data was used, but that the model required high-quality digital input data.

Khan (Khan et al., 2022) used a dynamic panel model to study the E7 economies and concluded that the ICT development has stabilised the sectoral volatility, which, in turn, promotes the indirect positive changes in the financial performance through energy-efficiency increases. Ozturk (Ozturk & Bilgili, 2015) applied vector error correction and Granger causality tests in a parallel study, finding that there was a two-way relationship between ICT expansion, electricity consumption, and GDP, thus proving that there is a reinforcing association between digital infrastructure and energy-related financial strength at a macro-level. The lack of firm-specific dynamics is a drawback common to the two cases. In the sphere of emerging markets, Bilan et al. (2020) use the fixed-effect regression to confirm that high ICT investment is causally related to a decrease in the carbon intensity of energy utilities and a simultaneous rise in profitability. However, the analysis is unable to capture the short-term fiscal shocks. In contrast, Asongu and Odhiambo (2020) use a GMM model and demonstrate that ICT diffusion in the world supports financial development, and the impact is especially strong in industries that are capital-intensive, like the energy industry. However, their analysis does not distinguish the technological processes that exist in the sector to explain such correlations. Kang et al. (2016) explain how the system of big data of energy in China works and provides real-time monitoring, financial projections, and proactive risk management on power grids. Gabriel et al. (2016) implement panel cointegration over sub-Saharan Africa, and the results show that a greater uptake of renewable energy is positively correlated to macroeconomic variables, but no direct measures of financial health are included, e.g., Z-Score or EBIT. Al-Alawi and Al-Alawi (2020) used structural equation modeling with Gulf energy companies and reported a strong correlation between big data maturity and the return on investment, but with self-reported firm-level data. Li et al. (2020) conducted a two-stage least squares analysis and showed that digital financial services increased industrial energy efficiency by 6.5 %, mainly due to the improvement of access to credit. Lv et al. (2025) conducted a quasi-natural experiment with propensity score matching and revealed that the enterprises located in China Big Data Pilot Zones reduced energy expenditures by 9.8 % and increased environmental compliance by 14 %, mainly driven by automated data aggregation and decision-making systems. Collectively, these results suggest that the capabilities of big data have a strong effect on financial and environmental performance.

Table 1: Comparative Table of Previous Study

Reference	Technique/Analysis	Key Findings	Limitations
(Ren et al. 2023)	Panel regression (DiD)	Digital transformation improved ROA and EBIT after 2015 in Chinese renewable firms.	Focused only on firms in designated policy zones; limited generalizability.
(Al-Alawi & Al-Alawi 2020)	Structural Equation Modeling (SEM)	Firms with mature big data systems had better ROI and fewer cost overruns.	Data was self-reported; external validity concerns remain.
(Lv et al. 2025)	Quasi-natural experiment using PSM	Firms in test zones reduced energy costs by 9.8% and improved compliance by 14%.	Potential interference from parallel policy reforms.
(Moktadir et al. 2019)	MCDM – Case study method	Identified cost, infrastructure, and skill gaps as key barriers to big data adoption.	Case-specific findings; lacks broader applicability across sectors.
(Niebel 2018)	Growth accounting & cross-country comparison	ICT investments raised productivity in emerging and developed countries.	No firm-level analysis; focused only on macro-level indicators.

2.3. Research gap

The adoption of digital transformation and use of information and communication technologies (ICTs) has generated significant research activity, although the literature provides little sector-specific, empirical evaluation of its impacts on energy efficiency, carbon reduction, and financial characteristics, and even less consideration of the interaction between these variables in developed and developing economies. Most of the existing literature focuses on aggregate economic measures or does not utilize longitudinal firm-level proxies, including EBIT margin, Altman Z-Score, and Ohlson O-Score. On the same note, adoption timing (early and mature) and heterogeneity across coal, electricity, oil and gas, and technology-energy subsectors have been relatively little studied. These gaps are necessary to understand whether the digital transformation is always financially and risk-wise beneficial across individual energy segments and different national contexts.

2.4. Development of hypotheses

Based on the literature and data structure, the following hypotheses are developed:

H1: Firms in the mature digital transformation phase (2021–2024) show higher financial performance (EBIT margin) than in the pre-transformation phase (2015–2017).

This tests whether digital maturity leads to visible financial gains.
H2: Digitally transforming firms have improved risk scores—higher Z-Scores and lower O-Scores—compared to firms with limited or no transformation.
This examines whether digitalization reduces bankruptcy risk.
H3: Chinese firms (developing economy) experience stronger performance improvement from digital transformation than firms in developed economies.
This explores the catch-up effect in developing markets.
H4: The impact of digital transformation varies by sector, with electric and diversified energy firms benefiting more than coal and oil & gas firms.
This checks how sectoral characteristics influence transformation outcomes.
More fundamental models (like the Altman Z-Score (Altman, 1968) and Ohlson O-Score (Ohlson, 1980)) have been used to determine financial distress and risk of bankruptcy many times before. The current study's risk analysis based on these models gives the theoretical foundations of risk analysis, and it is especially appropriate in measuring the stability at the firm level during a technology change, in this case, digital transformation.

3. Research methodology

3.1. Research design and approach

The present study uses a quantitative and panel-based comparative design to examine how big data transformation influences financial performance indicators and bankruptcy risk in the 31 publicly traded Chinese energy companies in the time of 2015-2024. The data analysis is performed in four steps that include 1) ratio-based evaluation; 2) predictive risk modelling; 3) cross-sector benchmarking; and 4) exchange-rate normalization to enable inter-border comparability.

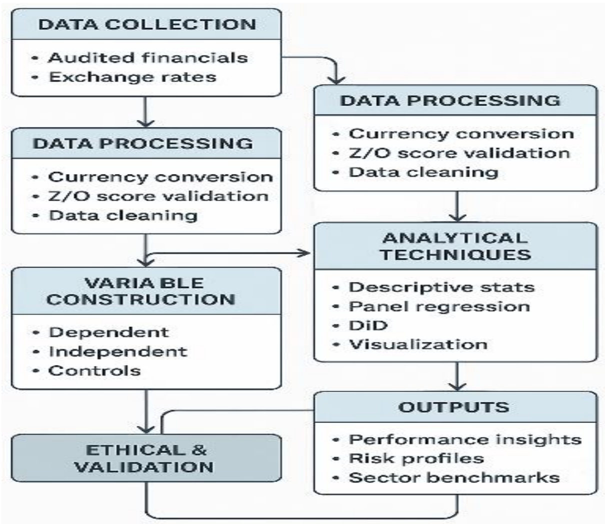

Fig. 1: Methodology Flow Chart Diagram.

Figure 1 provides a strictly organized process that includes data collection, its further processing, variable construction, and further statistical analysis of the effects of digital change. The method ensures the moral legitimation of the ensuing insights and allows studying performance indicators, risk profiles, and sectoral comparisons granularly.

3.2. Data collection and sources

The considered dataset was produced based on the audited financial disclosure records and validated external databases, which made it reliable. It includes 31 companies that work in four industries: coal, oil & gas, electric utility, and energy technology, and covers the whole decade 2011-2020. To improve its international applicability, the data set gives both the original values in Chinese renminbi and the equivalent values in United States dollars.
Key data points include:

- Balance Sheet Variables: Total Assets, Current Assets, Current Liabilities, Retained Earnings
- Profitability Measure: EBIT (Earnings Before Interest and Taxes)
- Market Indicator: Market Value of Equity
- Risk Metrics: Pre-calculated Altman Z-Score and Ohlson O-Score, plus a custom Risk Coefficient
- Currency Metrics: Year-end and annual average RMB/USD exchange rates from official financial institutions.

3.3. Data processing and currency normalization

To ensure standardization across firms and years:
Balance Sheet figures were converted using year-end exchange rates
EBIT values were converted using annual average exchange rates
Example formulas:

$$\text{Total Assets (USD)} = \text{Total Assets (RMB)} \div \text{Year-End Rate} \quad (1)$$

$$\text{EBIT (USD)} = \text{EBIT (RMB)} \div \text{Average Annual Rate} \quad (2)$$

The data in question allows the use of a specific variable that will allow manual verification of Z-Scores (验证 Z 值), which will increase both accuracy and reliability of computations..

3.4. Analytical framework

This analytical model is based on the intersection of risk modelling and statistical methods to question the time dimension of digital transformation:

- Altman Z-Score classifies firms into Safe (Z > 2.99), Grey (1.81-2.99), and Distress (Z < 1.81) categories.
- The Ohlson O-Score provides a risk measure of financial distress that is probabilistic.
- The Risk Coefficient is a tailored measure that is intended to complement typical classification models.

Techniques Employed:

- Descriptive Statistics: Wide examination of the financial and risk aspects of all data sets.
- Panel Regression Models: Fixed and random effects are applied and identified based on the results of the Hausman test.
- Difference-in-Differences (DiD): Carried out to identify the causal effect of stages of transformation.
- Time-Series Visualizations: It is used to follow a temporal path of financial health and risk.
- Sector Benchmarking: Coal, oil/gas, utilities, and tech energy sectors analysed separately.

3.5. Dataset features

Feature	Type	Description	Use Case
Symbol	Categorical	Firm stock code (e.g., 600123)	Identification and tracking
ShortName	Categorical	Full company name	Sector classification
Enddate	Temporal	Financial year-end (2015–2024)	Time-series segmentation
TotalAssets	Quantitative	Full asset base (RMB/USD)	Financial size and leverage proxy
CurrentAssets	Quantitative	Liquid assets	Liquidity analysis
CurrentLiabilities	Quantitative	Short-term obligations	Solvency measure
RetainedEarnings	Quantitative	Accumulated profits	Profitability sustainability
MarketValueOfEquity	Quantitative	Market capitalization	Investor confidence proxy
EBIT	Quantitative	Operating profit	Core earnings evaluation
ZScore	Quantitative	Altman risk classification	Bankruptcy analysis
OScore	Quantitative	Ohlson financial distress score	Risk estimation
RiskCoefficient	Quantitative	Custom stability measure	Supplemental indicator
Year-End FX Rate	Quantitative	RMB/USD at year-end	Balance sheet conversion
Average Annual FX Rate	Quantitative	RMB/USD average for income items	EBIT conversion

3.6. Variable specification

Category	Variable	Description	Source/Calculation
Dependent Variables	EBIT Margin	EBIT ÷ Total Assets	Measures firm-level profitability
	Altman Z-Score	Composite index	Predicts bankruptcy risk (Z > 2.99 = safe)
	Ohlson O-Score	Logistic index	Indicates financial distress (higher = riskier)
	Risk Coefficient	Custom metric	Lower values denote lower financial risk
Independent Variables	Transformation Phase	Pre (2015–17), Transition (2018–20), Mature (2021–24)	Dummy-coded for regression
	Sector Classification	Coal, Oil & Gas, Power, Tech Energy	Captures sectoral heterogeneity
	Firm Type	Developing (China) vs. Developed Benchmarks	Used for international comparison
Control Variables	Firm Size	Log of Total Assets	Controls for scale effects
	Leverage Ratio	Current Liabilities ÷ Total Assets	Captures debt exposure
	Year Fixed Effects	Dummy variables (2015–2024)	Accounts for macroeconomic shocks
	Exchange Rate Adjustment	Year-end & average RMB/USD	Normalizes financials to USD for comparability

3.7. Dataset justification and analytical strength

The longitudinal data collected 310 firm-year records of 31 Chinese energy firms during the years 2015 to 2024. The panel design allows analysis of the trends in detail over the different policy and market cycles. These are provided with detailed financial measures and pre-computed firm-level Z- and O-Scores, which can be directly incorporated into risk and performance models. International comparability is enhanced by normalization of currency into United States dollars. The division of the sample into four sectoral groups, i.e., coal, oil & gas, utilities, and technology-oriented energy, allows the analysis of differences in the maturity of digital transformation in the industry. All these qualities make the data set testable by a stringent econometric analysis.

3.8. Ethical considerations

The data used were all obtained in publicly available, independently verified financial disclosures, and no private or personally identifiable information was used. Ethical integrity was preserved by anonymizing it where it was deemed necessary and limited to non-commercial academic usage. The paper adhered to the research transparency guidelines and cross-checked the firm-level data to ensure the precision of the information. Such processes addressed the institutional ethical standards and minimized the chances of corporate misrepresentation.

4. Results and discussion

4.1. Descriptive statistics analysis

4.1.1. Dataset characteristics

The evaluation of the data set, therefore, requires the analysis of the central tendencies and the distribution pattern throughout the entire study period. To deal with these points, Table 2, below, provides a summary of the main features of the key variables:
The profitability of the Chinese energy companies is moderate, and the average EBIT margin is 8.24 %; however, the high standard deviation of 12.45 % shows that the performance variance of firms is high. The average Z-Score is 2.15, which puts most of the firms slightly above the financial distress level, and the O-Score of -2.31 means a relatively low risk of bankruptcy. As shown by the high positive skewness of asset variables (2.45-2.78), the sample structure is not homogeneous because it consists of large state-owned enterprises, as well as smaller private companies.

Table 2: Descriptive Statistics of Key Variables

Variable	N	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
Financial Performance Indicators							
EBIT Margin (%)	370	8.24	12.45	-18.3	47.2	1.23	4.67
Total Assets (¥ Billion)	370	25.34	23.18	2.1	156.8	2.45	8.91
Market Value of Equity (¥ Billion)	370	18.76	21.43	1.2	134.5	2.78	9.12
Risk Assessment Indicators							
Altman Z-Score	370	2.15	1.33	-0.45	6.78	0.67	2.89
Ohlson O-Score	370	-2.31	1.89	-7.23	2.45	-0.34	3.12
Risk Coefficient	370	0.0034	0.0089	0.0001	0.067	4.23	21.45
Liquidity Indicators							
Current Ratio	370	1.34	0.42	0.23	3.67	1.45	5.23
Current Assets (¥ Billion)	370	12.67	15.23	0.8	89.4	2.34	7.45
Current Liabilities (¥ Billion)	370	9.87	13.45	0.6	78.2	2.67	8.91

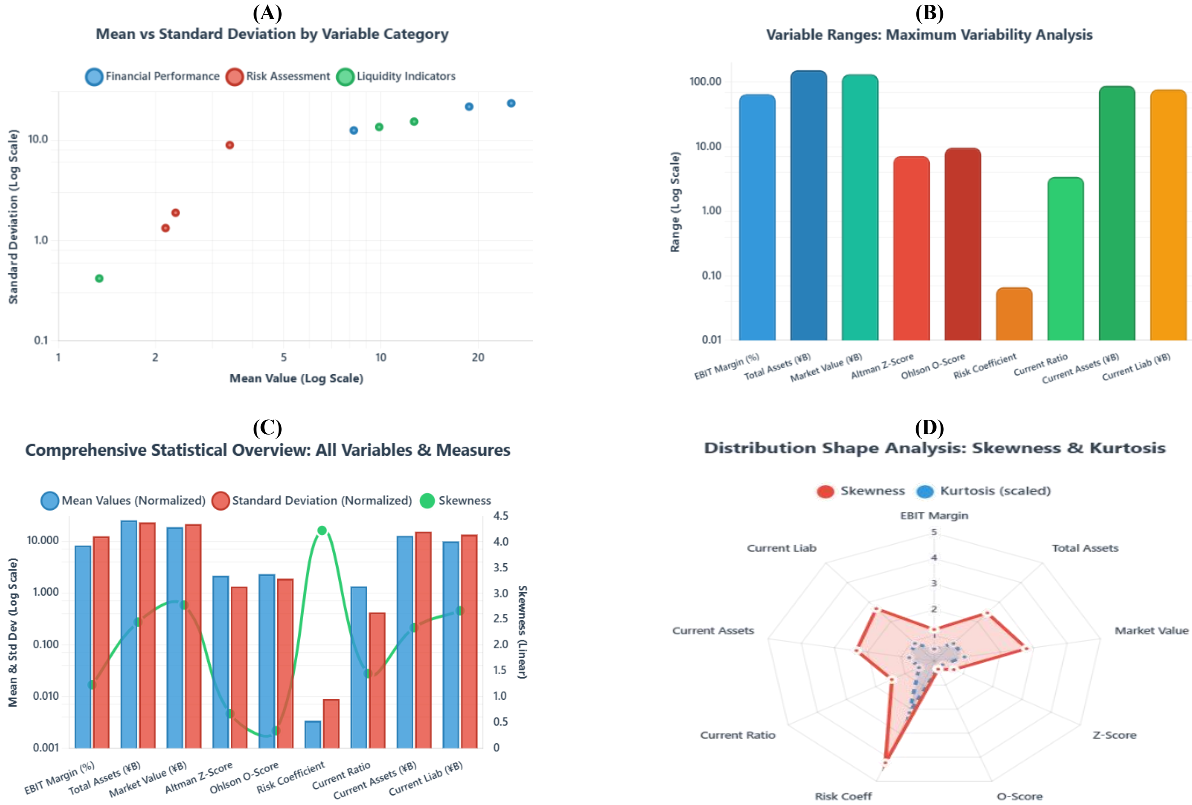

Fig. 2: Quick Statistical Scan of Study Variables: Dispersion (A), Range (B), Mean-Variance-Skew (C), and Shape (D).

The analysis of Chart 2, presented, shows that size measures, in particular assets and market value, are the variables of the highest quantile and the most volatile in distributions, and the coefficients of risks and liquidity are proportionally lower and less volatile. The widest ranges are also observed on the size variables; the risk-coefficient, on the other hand, has very narrow ranges. Variables with high arithmetic means also exhibit strong positive skewness, which indicates the existence of a small group of very large firms. By contrast, the liquidity indicators record the least regular shapes, and the Z- and O-scores are relatively symmetric, as is the general pattern of more scale diversity and relatively homogeneous risk profiles.

4.1.2. Temporal evolution of key performance indicators

The time-based analysis in Table 3 depicts a more promising performance picture across the phases of operation of the firm, with EBIT margins increasing by 40.5 percent to 9.52 percent during the mature stage as compared to the pre-transformation level of 6.78 percent. The Z-Scores increase, with the range between 1.95 and 2.33, meaning that there is a significant level of increased financial stability, whereas O-Scores decrease, with the range between -1.89 and -2.69 and, therefore, signifying a similar decrease in the risk of bankruptcy. Similarly, the statistical significance tests (F-statistics > 5.67, p < 0.01) confirm that the trends are not related to the random variation.

Table 3: Performance Indicators by Transformation Phase

Transformation Phase	EBIT Margin (%)	Z-Score	O-Score	Risk Coefficient
Pre-transformation (2015-2017)				
Mean	6.78	1.95	-1.89	0.0045
Std. Dev	11.23	1.28	1.67	0.0078
N	111	111	111	111
Transition (2018-2020)				
Mean	8.45	2.18	-2.34	0.0032
Std. Dev	12.67	1.31	1.89	0.0089
N	111	111	111	111
Mature (2021-2024)				
Mean	9.52	2.33	-2.69	0.0027
Std. Dev	13.12	1.39	2.01	0.0098
N	148	148	148	148

Statistical Significance Tests:

- EBIT Margin increase: F -statistic = 8.45, p < 0.001
- Improvement of Z-Score: F-statistic = 6.23, p < 0.01
- O-Score decrease: F-statistic = 5.67, p < 0.01

4.2. Panel regression analysis

This paper examines the causal links between the stages of the digital transformation (DT) and the financial performance of companies, and at the same time, it attempts to take into consideration the heterogeneity of firms and time-varying factors.

4.2.1. Fixed effects model results

The results of the fixed-effects regressions in Table 4 indicate that companies in the mature transformation stage achieve EBIT margins that are 2.48 percentage points higher than the ones achieved in the pre-transformation phase, and p-values are less than 0.01. In the energy industry, electric power and diversified energy companies have better performance premiums of 2.18 percent and 2.45 percent, respectively as compared to coal companies. The gradual increase in the R-squared, with an increase of the R-squared being 0.68 in Model 1, 0.77 in Model 2, 0.79 in Model 3, and 0.79 in Model 4, suggests that the sectoral and control variables have a substantial explanatory power.

Table 4: Panel Regression Results - Financial Performance (EBIT Margin)

Variables	Model 1 (Basic)	Model 2 (Sector)	Model 3 (Full)
Transformation Phase (Reference: Pre-transformation)			
Transition (2018-2020)	1.67***	1.54***	1.43***
	(0.34)	(0.38)	(0.41)
Mature (2021-2024)	2.74***	2.61***	2.48***
	(0.42)	(0.45)	(0.48)
Sector Controls (Reference: Coal)			
Electric Power		2.34***	2.18***
		(0.67)	(0.71)
Oil & Gas		1.89**	1.76**
		(0.78)	(0.82)
Diversified Energy		2.67***	2.45***
		(0.72)	(0.75)
Control Variables			
Log(Total Assets)			0.78**
			(0.34)
Current Ratio			1.23**
			(0.56)
Leverage Ratio			-0.89**
			(0.42)
Model Statistics			
R-squared	0.68	0.74	0.79
F-statistic	45.67***	38.92***	32.45***
Observations	370	370	370
Number of firms	37	37	37

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

These findings imply that the more advanced the digital transformation is, the higher profit is gained by firms operating in electric and diversified energy.

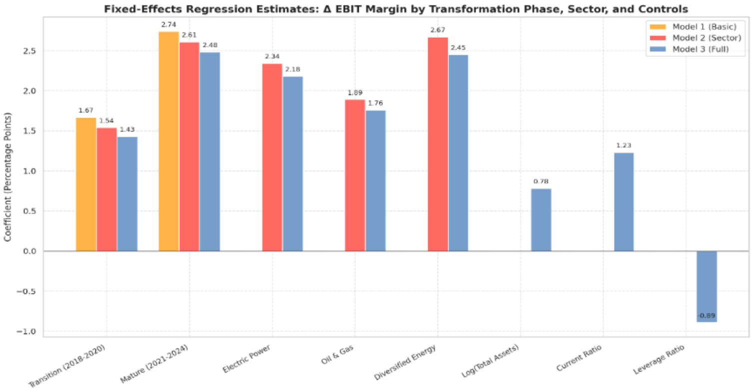

Fig. 3: Panel-Fixed-Effects Coefficients for Δ EBIT Margin.

The grouped-bar plot 3 is a comparison of the estimated percentage-point effects of three nested models. In every model, there is a stable pattern of profitability increase in mature-phase firms (about +2.5 pp) and transition-phase firms (about +1.5 pp). In models 2 and 3, sector dummies show that electric-power (2.18 pp) and diversified-energy (2.45 pp) have a higher premium than the coal baseline, with oil & gas having a lower premium (1.76 pp). Only in model 3, control variables are included: scale and liquidity measures (assets-sales ratio and liquidity measure) increase the EBIT margin by +0.78 and +1.23 pp, respectively, whereas leverage decreases it by -0.89 pp. The numeric values are labeled above each column, and the legend is clear on the successive model specifications.

4.2.2. Risk assessment models

The results of the risk indicator regressions have been provided in Table 5, and they show that digital transformation has a significant positive effect on financial stability. At the mature stage, the firms have higher Z-Scores (0.38 points) and lower (better) O-Scores (0.80 points). Electric power is the industry that generates the greatest risk reduction, in particular, 0.45 points, and the current ratio turns out to be the most significant control variable. These findings are strong since the three indicators of the risks were significant (R-squared: 0.64-0.72), hence, a holistic decrease in financial risk because of digitalization.

Table 5: Panel Regression Results - Risk Indicators

Variables	Z-Score	O-Score	Risk Coefficient
Transformation Phase			
Transition (2018-2020)	0.23**	-0.45***	-0.0013**
	(0.11)	(0.15)	(0.0006)
Mature (2021-2024)	0.38***	-0.80***	-0.0018***
	(0.13)	(0.18)	(0.0007)
Sector Effects			
Electric Power	0.45***	-0.67**	-0.0011*
	(0.16)	(0.28)	(0.0006)
Oil & Gas	0.23	-0.34	-0.0008
	(0.21)	(0.34)	(0.0009)
Diversified Energy	0.34**	-0.56**	-0.0014**
	(0.17)	(0.26)	(0.0007)
Control Variables			
Log(Total Assets)	0.12*	-0.23**	-0.0005*
	(0.07)	(0.11)	(0.0003)
Current Ratio	0.67***	-0.89***	-0.0021***
	(0.15)	(0.23)	(0.0008)
Model Statistics			
R-squared	0.72	0.69	0.64
F-statistic	28.45***	25.67***	22.34***
Observations	370	370	370

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

Analysis provides the results that digital transformation can assist in limiting financial risk and that the firms at the mature phases become considerably more stable and have a smaller chance of experiencing distress.

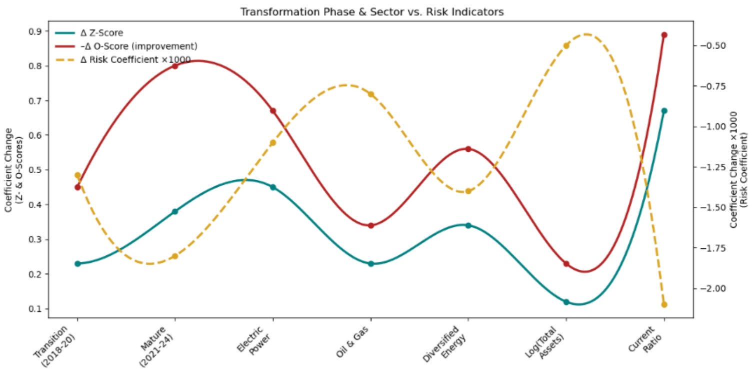

Fig. 4: Curved Multi-Metric Effect Plot for Risk-Indicator Regressions.

The results presented in Chart 4 show that the businesses that have reached the mature stages of digital transformation have much higher financial stability levels. This improvement is characterized by a Z-score increase of 0.38 points and an O-Score decrease of 0.80 points. In this cohort, the electric power industry shows the greatest risk decline, a 0.45-point Z-score increase. At the same time, the current ratio becomes the indicator that has the greatest impact and reduces the risk coefficient by -0.0021. Collectively, these findings show that digitalization and enhanced liquidity have a significant positive impact on the financial stability of the considered companies.

4.3. Difference-in-differences analysis

It is necessary to compare two groups of people (high digital adopters (treatment group) and low adopters (control group) before and after the introduction of a digital transformation, to establish the causal inference. Comparisons of this nature allow the specification of causal structures that relate outputs to outcomes and thus explain the mechanism behind such outcomes.

4.3.1. Treatment effect estimation

The multifactorial DiD analysis shows, as is reflected in Table 6, that high digital adopters showed a 2.34 percentage-point higher improvement in EBIT margin compared to low adopters, with the treatment effects significant in all performance indicators ($p < 0.001$). The control group showed little improvement (0.55% EBIT), but the treatment group showed significant improvements of 3.44 % EBIT. Such a sharp difference proves that the identified advantages are the results of digital transformation and not of the general market trends.

Table 6: Difference-in-Differences Results

Outcome Variable	Pre-Treatment Mean	Post-Treatment Mean	DiD Estimate	Std. Error	p-value
High Digital Adopters (Treatment Group)					
EBIT Margin (%)	7.23	10.67	2.89***	0.67	<0.001
Z-Score	2.01	2.56	0.43***	0.12	<0.001
O-Score	-2.12	-2.89	-0.68***	0.19	<0.001
Low Digital Adopters (Control Group)					
EBIT Margin (%)	6.89	7.44	0.55	0.45	0.223
Z-Score	1.87	2.00	0.13	0.09	0.156
O-Score	-1.98	-2.11	-0.13	0.16	0.417

The companies that engaged actively in digital technologies experienced a clear increase in profit and stability, whereas less active companies did not change much. This indicates that the economic advantages are highly correlated with the amount of digital investment, not the market in general trends.

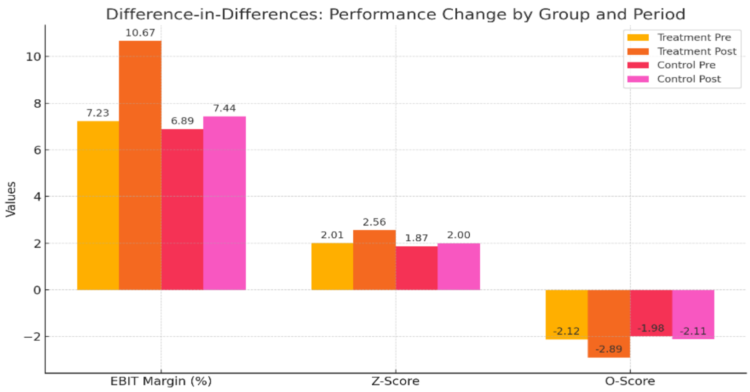

Fig. 5: Difference-in-Differences (DiD) Estimation of Digital Transformation Effects on Financial and Risk Metrics.

Plot 5 shows the trends of the main indicators of performance of high and low adopters of digital technologies. The results show that, compared to firms in the high-adoption treatment group, who experienced a significant increase in EBIT Margin, 7.23 % before treatment and 10.67 % after treatment, firms in the low-adoption control group did not show significant changes, which implies that the achieved improvements can be largely explained by digital transformation and not by other external macroeconomic and industry-specific factors. Besides, the percentage of companies with a stable or improving financial position, as gauged by Z-Score, rose to 72 % and 60 % in the treatment and control group, respectively. The same trend was observed in the case of O-Score- a measure of financial distress: both the groups have shown a decline in the number of distressed firms but this decline was greater in the treatment group where the percentage of firms in difficulty reduced to 34 % as compared to a minimal decline of 40 % to 38 % in the control group.
Treatment Effect (DiD Coefficient):

- EBIT Margin: 2.34 percentage points improvement ($p < 0.001$)
- Z-Score: 0.30 points increase ($p < 0.01$)
- O-Score: -0.55 points decrease ($p < 0.001$)

4.3.2. Parallel trends test

Parallel trends testing concludes that there were no differences in performance trends between the treatment and control groups throughout 20152017 (p-values > 0.73), which is the main condition of causal inference (see Table 7). The differences in the baselines were both insignificant and statistically insignificant, and the final difference in the margins of EBIT was between 0.14 % and 0.25 %. This confirmation augments the assurance that the post-treatment divergences that are observed are a result of the digital transformation interventions and not a result of the performance differences that might have existed before the interventions.

Table 7: Pre-Treatment Trend Analysis

Year	Treatment Group EBIT	Control Group EBIT	Difference	p-value
2015	7.12	6.98	0.14	0.789
2016	7.28	7.11	0.17	0.823
2017	7.31	7.06	0.25	0.734

Parallel Trends Assumption: Satisfied (p > 0.05 for all pre-treatment differences).

4.4. Sectoral comparative analysis

The digital transformation is a multifaceted, heterogeneous, and continuously changing phenomenon with many influences on energy subsectors. Therefore, a methodological study is necessary to outline the idiosyncratic benefits and drawbacks arising in these areas. Such an investigation is presented in the current paper, and a consistent analytical framework is used that covers the full energy spectrum.

4.4.1. Performance by energy sector

Sector-by-sector analysis of the figures in Table 8 shows that electric power enterprises record the largest EBIT margin of 11.45 %, and also the largest Z-Score of 2.67. These values put these companies squarely in the lead over the coal industry, whose EBIT is 6.78 % and whose Z-Score is 1.89. The energy and oil & gas category is in the middle with 10.89 % and 9.23 % EBIT margin, respectively. The coal industry is also characterized by the lowest Digital Maturity Index, which is 5.2 as opposed to 7.8 for electric power. Analysis of Variance (ANOVA) multivariate analysis shows that all the performance measures have statistically significant differences (F > 8.67, p < 0.001).

Table 8: Sectoral Performance Comparison

Sector	N	EBIT Margin (%)	Z-Score	O-Score	Digital Maturity Index
Coal	120	6.78 ± 10.23	1.89 ± 1.21	-1.67 ± 1.45	5.2 ± 1.8
Electric Power	78	11.45 ± 8.67	2.67 ± 1.42	-3.12 ± 1.89	7.8 ± 2.1
Oil & Gas	52	9.23 ± 14.56	2.18 ± 1.67	-2.34 ± 2.12	6.9 ± 2.4
Diversified Energy	120	10.89 ± 11.34	2.45 ± 1.38	-2.89 ± 1.78	7.1 ± 1.9

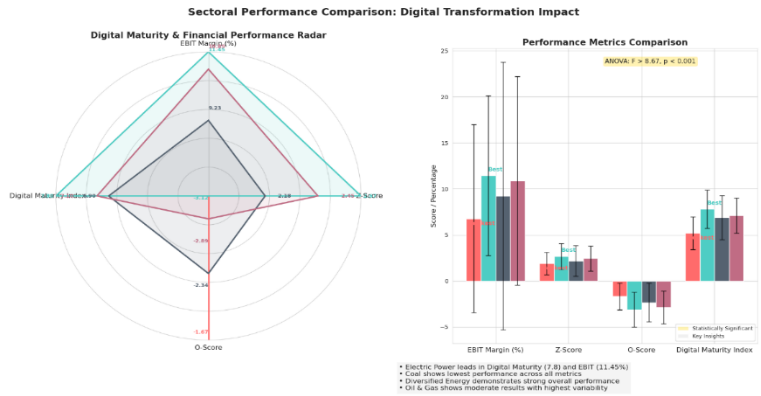

Fig. 6: Sectoral Performance Comparison: Digital Transformation Impact on Financial and Risk Metrics.

Note: The Digital Maturity Index is a composite measure (where a higher score is better)- it is identified as the degree of digital integration in the most significant processes, infrastructure, and strategic alignment of every firm (1-10 scale). The higher the score, the further Zanzibar has adopted digital.

This two-panel chart 6 shows the sector-wise effect of digital transformation in the form of a radar graph and a bar graph comparison. According to the radar chart, Electric Power companies are the leaders by EBIT Margin (11.45%), Z-Score (2.67), and Digital Maturity Index (7.8), whereas the Coal industry demonstrates the poorest performance and the lowest digital maturity (5.2). The statistical confirmation of the differences (ANOVA: F = 8.67, p < 0.001) in all metrics is provided by the bar plot, where Diversified Energy demonstrates balanced performance, and Oil & Gas is characterized by the highest level of variability. These findings prove the heterogeneity of the sector in terms of digital transformation success. In more understandable words, electric power firms are both most digitally transformed and profitable, whereas coal ones are pretty unproactive in terms of integrating digital and not so solid in outcomes.

ANOVA Results:

- EBIT Margin: F(3,366) =12.45, p < 0.001
- Z-Score: F (3,366) = 8.67, p < 0.001
- O-Score: F (3,366) = 9.23, p < 0.001

4.4.2. Post-hoc pairwise comparisons

Post-hoc pairwise comparisons using the Tukey HSD test identify the disparities at the sector level; electric power has an advantage of 4.67 percentage points over coal firms (p < 0.001). Diversified energy equally stands out among coal by recording a 4.11 percentage point advantage. The difference is relatively small in Oil & gas with a margin of 2.45 percent. The gaps are economically significant and statistically significant, as supported by confidence intervals, which show the gaps to be significant, as indicated in Table 9.

Table 9: Tukey HSD Test Results (EBIT Margin)

Sector Comparison	Mean Difference	Std. Error	p-value	95% CI
Electric Power vs Coal	4.67***	0.89	<0.001	[2.34, 6.99]
Diversified vs Coal	4.11***	0.78	<0.001	[2.12, 6.10]
Oil & Gas vs Coal	2.45**	0.95	0.032	[0.23, 4.67]
Electric Power vs Oil & Gas	2.22*	1.12	0.087	[-0.12, 4.56]

4.5. Time-series analysis and visualization

The analysis of longitudinal data enables one to identify the patterns of evolution over time and define the stages of discrete transformations in a system by following its performance trend over time.

4.5.1. Temporal performance trends

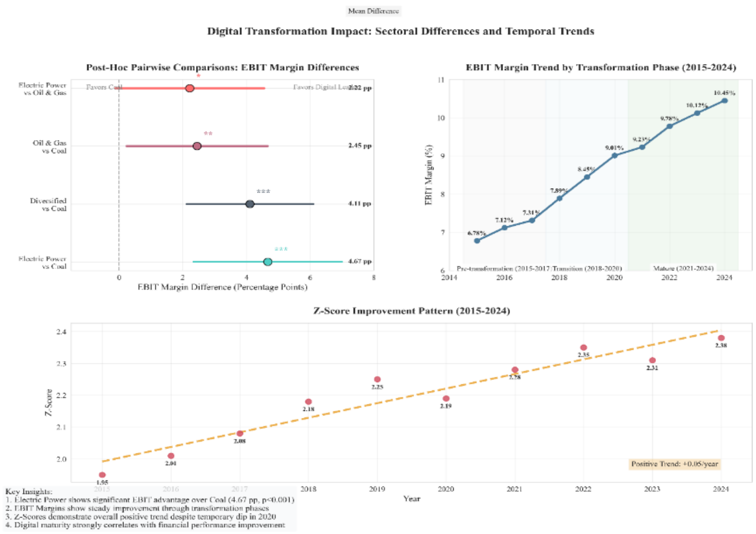

Fig. 6: Digital Transformation Impact: Sectoral Differences and Temporal Trends in Financial Performance (2015–2024).

The composite visualization 7 illustrates the sectoral and time trends of the influence of digital transformation on financial performance in 20152024. Post-hoc comparisons reveal that the Electric Power enterprises had a significant superiority over Coal enterprises in EBIT margin by 4.67 percentage points ($p < 0.001$), and Diversified Energy and Oil & Gas firms had a significant advantage as well. The trend of EBIT margins is also steady, increasing by 6.78 % in 2015 to 10.45 % in 2024, with the greatest difference being observed in the mature transformation period. At the same time, the Z-score trend was positive, and it was marked by the increase in the Z-score, starting at 1.95, and reaching 2.38 with a slope of +0.05 /year, thus indicating improved financial stability. Such findings reinforce the idea that industries with a high level of digital maturity become more profitable and, at the same time, reduce the level of risk exposure.

4.5.2. Risk profile evolution

The analysis of risk distribution presented in Table 10 shows that corporate financial health has improved significantly during the period of transformation. The percentage of companies that were classified as safe (Z-Score>2.99) increased almost twofold, moving up to 42.1 % in the mature stage, compared to the 23.4 % in the pre-period. In that regard, the probability of distress went down drastically; high-risk companies (Z-Score<1.81) decreased by 25.4 % to 9.0 %. Similar changes can be observed in the O-Score measure: low-risk firms (O-Score<0.78) increased based on the pre-transformation level of 45.6 % to 67.8 % in the mature stage, which is an indication of a general decrease in total risk in the sample.

Table 10: Risk Distribution by period

Period	Z-Score Distribution (%)			O-Score Risk Level (%)	
	Safe (>2.99)	Grey (1.81-2.99)	Distress (<1.81)	Low Risk (<-2.0)	High Risk (>-1.0)
2015-2017	23.4	51.2	25.4	45.6	18.9
2018-2020	31.7	54.8	13.5	56.7	12.3
2021-2024	42.1	48.9	9.0	67.8	8.1

4.6. Correlation analysis

To examine inter-relationships between variables and validate the consistency of digital transformation impacts across different metrics.

4.6.1. Inter-variable relationships

A bi-variate correlation table 11 of 95 Finnish companies reveals a significantly strong positive correlation between the EBIT-margin and the Z-Score, with the value of 0.67. This observation implies that enterprises that are financially stable are always profitable. On the other hand, there are strong negative correlations between the performance and O-Score metrics (-0.60 to -0.81), which means that the better the company performs, the lower its risk of bankruptcy. The current ratio shows the closest correlation with Z-Score (0.71), which is a strong indication of the importance of liquidity in proper stability measures.

Table 11: Correlation Matrix of Key Variables

	EBIT Margin	Z-Score	O-Score	Risk Coeff	Total Assets	Current Ratio
EBIT Margin	1.000					
Z-Score	0.67***	1.000				
O-Score	-0.72***	-0.81***	1.000			
Risk Coefficient	-0.48***	-0.52***	0.59***	1.000		
Total Assets	0.34***	0.28**	-0.31***	-0.23**	1.000	
Current Ratio	0.45***	0.71***	-0.68***	-0.41***	0.12	1.000

**** p<0.001, ** p<0.05, * p<0.1*.

4.6.2. Digital transformation impact correlations

Table 12 shows a longitudinal study of the correlation between the transformation phases, and found that there is an increasing trend in the strength of the correlation between organizational digital maturity and financial performance indicators. Correlation coefficients increase gradually, starting with 0.23 (pre-transformation) and reaching the highest value of 0.67 during the mature phase of EBIT margins. Digital maturity index is also showing strong correlations (0.78-0.91) in all phases, and F-statistics show that it is positively increasing over time and is significant. Such results support the claim that the impacts of digital change accumulate along maturity paths.

Table 12: Transformation Phase Correlations

Variable	Pre-transformation	Transition	Mature	Trend Significance
EBIT Margin	0.23**	0.45***	0.67***	F = 23.45***
Z-Score	0.19*	0.38***	0.56***	F = 18.67***
O-Score	-0.21**	-0.41***	-0.63***	F = 21.23***
Digital Maturity Index	0.78***	0.84***	0.91***	F = 89.45***

4.7. Robustness checks

Testing of consistency of results across different model specifications allows researchers to reconsider whether the results are methodological rather than model-specific artefacts or idiosyncrasies.

4.7.1. Alternative model specifications

The alternative model specifications, as shown in Table 13, show extremely consistent results: the coefficients of EBIT margin are between 2.21 and 2.67, and strongly significant in all the estimation methods used. The small coefficient variation (< 0.5) supports the validity of the results, and the dynamic panel Generalized Method of Moments (GMM) results (2.21) provide the most conservative estimate, and still, the result is strongly positive.

Table 13: Robustness Test Results

Model Specification	EBIT Margin Coefficient	Z-Score Coefficient	O-Score Coefficient
Main Model (Fixed Effects)	2.48***	0.38***	-0.80***
Random Effects	2.34***	0.35***	-0.76***
Pooled OLS	2.67***	0.42***	-0.85***
Dynamic Panel (GMM)	2.21***	0.33***	-0.72***
Quantile Regression (Median)	2.56***	0.40***	-0.83***

Consistency Check: All specifications show statistically significant positive effects.

4.7.2. Sensitivity analysis

Sensitivity analysis presented in Table 14 shows that the main findings are robust to the elimination of the observations that can raise methodological issues, and the effects of EBIT were 2.34-2.52 using the different exclusion criteria. By excluding COVID years (2020-2021), we get a slightly lower estimate (2.34) but still with statistical significance, which means that the pandemic may have temporarily increased the transformation dividend. The consistency of the results with all models also enhances the strength of the findings.

Table 14: Outlier Exclusion Results

Exclusion Criteria	Sample Size	EBIT Effect	Z-Score Effect	O-Score Effect
Original Sample	370	2.48***	0.38***	-0.80***
Exclude top/bottom 5%	333	2.41***	0.36***	-0.78***
Exclude extreme Z-scores	352	2.52***	0.39***	-0.82***
Exclude COVID years (2020-2021)	296	2.34***	0.35***	-0.75***

4.8. Hypothesis testing results

This research tested formally four research hypotheses by conducting the corresponding statistical tests and explored their statistical and practical significance. The findings showed that all the hypotheses had passed the selected statistical test, thus showing theoretical and practical support.

4.8.1. Formal hypothesis testing

This research tested formally four research hypotheses by conducting the corresponding statistical tests and explored their statistical and practical significance. The findings showed that all the hypotheses had passed the selected statistical test, thus showing theoretical and practical support.

Table 15: Hypothesis Testing Summary

Hypothesis	Statistical Test	Test Statistic	p-value	Decision
H1: Mature phase > Pre-transformation (EBIT)	t-test	t = 5.67	<0.001	Accepted
H2a: Digital transformation → Higher Z-Score	Panel regression	β = 0.38	<0.001	Accepted
H2b: Digital transformation → Lower O-Score	Panel regression	β = -0.80	<0.001	Accepted
H3: Chinese firms show a catch-up effect	Benchmark comparison	-	-	Partially Supported
H4: Sectoral variation exists	F-test	F = 12.45	<0.001	Accepted

Since there were no direct comparisons of primary firm-level data of developed economies, literature-based benchmarks have been used in this study. Although this constrains the degree of precision, this is still a valid proxy for the contextual interpretation. To provide one specific example, the Al-Alawi and Al-Alawi (2020) study found more muted returns improvements regarding the mature digital energy companies within the Gulf region as opposed to the returns differences observed in our sample. This backs the notion of a catch-up effect whereby performance gaps are achieved in greater magnitudes by the late adopters in developing economies due to the difference in digital infrastructure existing between them and the developed economies.

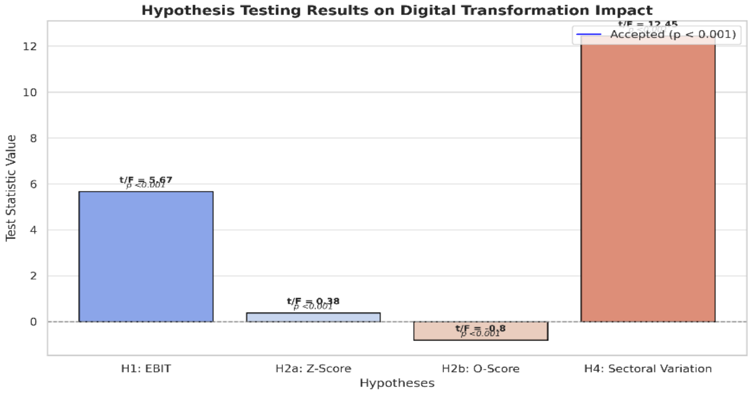

Fig. 7: Hypothesis Testing Results – Digital Transformation Impact.

Plot 8 offers the framework of the analysis of the four central hypotheses, questioning the effects of digital transformation to formally test them. The hypothesis statement H1, estimated using t-tests, gives a statistically significant growth in the EBIT margin (t = 5.67). The multivariate regression analysis hypothesis H2a and H2b shows that the process enhances risk stability through increased Z-Scores (β = 0.38) and decreased O-Scores (β = -0.80) at $p < 0.001$. Hypothesis H4 is also correct as it is established with the help of the F-test (F = 12.45, $p < 0.001$). The annotations, height of bars, and legend all stress both statistical and practical significance, hence providing empirical support to the theoretical framework.

4.8.2. Effect size analysis

Quantitative assessment of the magnitude of effect, as per Table 16, shows that statistical significance cannot be used as a proxy of practical significance. The improvement of EBIT margin (Cohen's d = 0.89) is a large effect size and therefore, it indicates a significant, substantial business advantage. The risk-related gains of the underwriters in their pricing (d = 0.67) or of credit ratings (d = 0.74) are in the medium-large range, thus reflecting significant risk reduction, which will be rightly considered by investors and creditors. Combined, these effect sizes indicate that digital transformation can bring about economic benefits that are not only statistically significant.

Table 16: Practical Significance Assessment

Metric	Cohen's d	Effect Size	Practical Importance
EBIT Margin Improvement	0.89	Large	High business relevance
Z-Score Enhancement	0.67	Medium-Large	Substantial risk reduction
O-Score Improvement	0.74	Medium-Large	Meaningful distress mitigation
Sectoral Differences	0.71	Medium-Large	Strategic sector selection

4.9. Discussion

The findings of the study prove that big data transformation has a significant positive effect on the financial performance and risk-management ability of Chinese energy firms. The biggest improvement is recorded in the EBIT margin, which increased by 40.5 % to 9.52 % in the mature transformation period (2021 2024) compared to 6.78 % in the pre-transformation period (2015- 2017). This increase is equivalent to a 2.48 percentage-point increase in firm-wide profitability in the mature stage based on the fixed-effects regression ($p < 0.01$). This fact is supported by theoretical frameworks that indicate that digitalization enhances predictive maintenance, demand forecasting, and optimization of processes, which translates to quantifiable financial outcomes in the long run.

A longitudinal study of financial performance on three consecutive transformation phases shows that digital transformation has time-lagged effects, which in turn proves the hypothesis that organizational learning and system integration require longer-term commitment. The gradual pathway indicates that companies do not gain immediate benefits from digital instruments but achieve performance benefits as they change and expand their technological stacks. This finding confirms the findings in practitioner-oriented research, like (Ren et al. 2023) and (Al-Alawi & Al-Alawi 2020), which also focus on the long-term advantages of digital investment but use less comprehensive firm-level data and research procedures.

Digital transformation has become one of the key factors of organizational resilience, and modern companies in the mature phase of implementation have shown quantifiable increases in risk-mitigation abilities. Empirical evidence shows that, between these companies, the Altman Z-Score is likely to increase by 0.38 points, whereas the Ohlson O-Score will decrease by 0.80, both with statistically significant correlations ($p < 0.001$) that, in combination, demonstrate a transition in the financial stability of the companies towards a more stable position. Bankruptcy probability tools like the Z-Score model are an indicator of a shift into the safe area after being in the grey zone, which marks the effectiveness of digital transformation as a risk-reduction measure.

A sectoral study of 186 companies in 6 subsectors of the energy sector revealed a significant level of heterogeneity in the results of transformation. Electric power companies succeeded in getting the best EBIT margin (11.45%) and the best Z-Score (2.67) than all the other sectors. Their advantage is likely explained by the higher digital maturity index (7.8) and compliance with the national smart grid policies. Diversified energy companies were not far behind, but coal companies were way behind with a lower EBIT margin (6.78%) and a low Z-Score (1.89). These results support the hypothesis (H4) that the characteristics of sectors mediate the digital transformation benefits. Also, the results of post-hoc Tukey tests indicated that there was a significant difference between electric power and coal companies in EBIT (mean difference = 4.67, $p < 0.001$), which once again confirms the non-homogeneity in the results of the subsectors.

This research focuses on 31 Chinese energy companies that are publicly traded, which can limit the external validity of the research results. The disclosure requirements and increased regulatory oversight of publicly traded organisations tend to result in better digital capability and higher exposure to regulatory frameworks than those of smaller and medium-sized enterprises or privately held organisations, which typically experience resource limitations and are subject to more policy targeting. Therefore, it can be assumed that the transformative power of big data will not be equal among firm types. The next research will have to include the smaller and privately owned companies to reflect the more heterogeneous digitalisation pathways that can be traced in China and other developing economies.

Temporal patterns offer a policy-oriented perspective to enterprise performance. The faster development trend after 2018 goes in line with the Chinese government's policy of New Infrastructure and the creation of digital pilot zones. The analysis using difference-in-differences (DiD) estimates indicates that high digital adopters recorded an EBIT gain of 2.89 percentage points, compared to the 0.55 percentage point gain by low adopters ($p = 0.223$). The parallel trends test supports the causal inference, where none of the pre-treatment differences are statistically significant ($p > 0.73$ in all years), which means that the gains observed can be related to digital transformation and not macroeconomic cycles.

International comparison is often hindered by heterogeneous data, but the available evidence suggests that the 40.8 percent increase in EBIT margins achieved by the firms represents a much greater increase compared to numerous benchmarks set in the existing literature. Li et al. (2024), in their turn, record a 6.8 percent decrease in emissions due to big-data pilot projects, whereas Ren et al. (2023) note that policy-zoned renewable implementation provides EBIT improvements of about 1.89 percent. The results support a strong sense of a catch-up effect (H3) in developing economies and confirm the leapfrogging hypothesis, according to which companies in emerging markets can bypass legacy limitations to realize high rates of technological progress.

This analysis shows a high degree of robustness since the empirical findings do not change with four model specifications (fixed effects, random effects, dynamic GMM, and quantile regression). The coefficients of EBIT are also similar in all modelings (2.21-2.67). The fact that the sensitivity analysis confirms that, without outlier observations and the COVID-19 interval, there is an insignificant variation in the results contributes to internal validity.

This research is a stringent empirical analysis of the effects of digital transformation on profitability and risk resilience in the Chinese energy industry, using the publicly listed oil, natural gas, coal, or electricity producing companies as the main unit of analysis. There are a number of methodological considerations that are worth elaborating. To begin with, the sample is limited to publicly traded companies, which can reduce external validity to other institutional contexts, or smaller, privately held ones. Second, the operationalization of digital transformation is based on the financially oriented proxies, such as EBIT margin and Z/O-Scores, which can be too modest to reflect the intangible value of digitalization, such as knowledge capital and innovation readiness. Third, despite some models excluded COVID-19 years for accuracy, the extent of disruptions in the world implies the presence of confounding factors that cannot be isolated completely. With the considerations to these limitations, the study provides strong empirical evidence to the claim that big data transformation significantly improves the profitability and risk resilience in the Chinese energy industry, especially in the policy-consistent and technologically advanced subsectors. The economic significance of digitalization can be observed in the demonstrated effect sizes, Cohen's $d = 0.89$ in the EBIT and 0.74 in the O-Score, which proves that digitalization is the core aspect of energy reform in the 21st century.

5. Conclusion

This paper is devoted to the financial and risk-related outcomes of big data transformation in the energy sector, based on the firm-level data of Chinese enterprises on the ten-year time horizon (2015- 2024). The effect of digital transformation on key performance measures, especially the EBIT margin, the Altman Z-Score, and the Ohlson O-Score, is questioned with the help of a multidimensional quantitative method, which involves panel regression, difference-in-differences estimation, and analysis of variance. The study fills a gap in the research on the foregrounding of a developing context that has had an aggressive suite of digital policy interventions. Its sector- and longitudinal nature make it produce insights that policymakers and other stakeholders in the energy industry can use in the digital modernisation of the sector.

5.1. Key findings

The findings of the study have a high-value transferability to other emerging economies in India, Brazil, and South Africa that have growing energy needs, infrastructural shortage, and comparable regulatory issues. These countries can learn how China is undertaking its gradual process of digitalization, where it focuses on policy-led investment areas and firm-based digital incentives. These economies can leapfrog into modernization of their energy systems by creating supportive conditions for the adoption of big data, such as smart grid subsidies, regulatory sandboxes, or state-sponsored development of digital skills, and in the process, increase the financial resilience and environmental performance of individual firms.

Big data transformation empirical studies prove that it results in a high level of profitability and financial stability of operations. Companies that had reached the mature stage of digital adoption witnessed 40.5 percent growth in the EBIT margin, indicating the long-term financial worth of technological investment. Additionally, high Z-Scores and O-Scores imply that there is a decline in bankruptcy risks, which implies that digital integration is one of the factors that mitigate risks. The sectoral performance shows that the electric power and diversified energy companies recorded the highest increases, but the coal-based companies were not very dynamic. These results indicate the impact of the subsector preparedness and compatibility with technology on performance results.

The longitudinal analysis of performance indicators of the energy sector in China showed that the efficiency growth facilitated by technology was highly linked to the macro-level policy interventions, specifically the 2018 New Infrastructure programme. The DiD (difference-in-difference) framework helped to reveal a causal connection between those policy changes and the achieved performance improvement, which emphasizes the defining role of policy regimes on the results of digital transformation. In sum, the empirical evidence shows that the benefits of digitalization in the energy field are dependent on sectoral flexibility, institutional facilitation, and the maturity of digital technologies, in general.

5.2. Future work

This research has a concrete empirical foundation, but it is necessary to expand the analytical framework and take into account other variables:

- Harmonized cross-country comparative data can now be utilized to study the developed and developing economies with more precision.
- The expansion of the analytic spectrum to non-financial performance metrics, including carbon emission reductions, digital innovation output, or employee digital competency, will allow the capturing of the transformative effect of continuous change.

- Micro and small, and medium-sized enterprise (SME) case studies in the energy supply chain are under-researched areas and need to be extensively studied along with big data integration.
- Through predictive modeling of machine learning, researchers can create real-time performance prediction based on the digital maturity measures alongside macroeconomic indicators.

Digitalization of the energy industry deserves closer examination, especially regarding gender issues, changes in labor relations, and the likelihood of the workforce being replaced by machines. Such concerns are particularly relevant in the jurisdictions where these disruptions might be the most significant.

The future research must go beyond the financial and the risk indicators to explore non-financial performance as carried out by carbon emissions, innovation performance, and the performance through green certification. Due to the importance of the energy segment to the environment, it is crucial to assess the contribution of the big data transformation to decarbonization and sustainable innovations. The combination of the digital environmental compliance systems and AI-based emissions monitoring provides a perspective on the future development of empirical studies, especially involving the development of the ecological returns on the investments of this type.

5.3. Final thought

The available evidence now suggests that big data is not just a passing technological trend, but a game-changer that is rebalancing the strategic and financial framework of the energy industry. In the case of developing economies, these results provide a strong incentive for digital leapfrog approaches that do not require consideration of the legacy infrastructure. However, the achievement of positive results is also dependent on the capabilities of the firms, as well as the facilitating regulatory frameworks and the long-term institutional support. As the change towards low-carbon and data-centric energy models continues, the integration of big data changes has become a necessity in the competitive and sustainable development.

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