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Evaluating the Efficiency of AI-Driven Technology Companies in Taiwan Through ESG Practices Using Data Envelopment Analysis (DEA)

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ABSTRACT: This study examines the operational efficiency of AI-driven technology firms in Taiwan by incorporating Environmental, Social, and Governance (ESG) factors into a Data Envelopment Analysis (DEA) framework. Using quarterly data from 40 publicly listed firms between 2019 and 2024, the analysis employs the CCR DEA model to evaluate the conversion of financial and ESG-related inputs into performance outputs. Stepwise regression identifies gross margin ratio, total assets growth, and cash flow ratio as significant determinants of efficiency. Results reveal that firms with single-stage production processes and those listed on the Taiwan Stock Exchange exhibit higher efficiency levels. While ESG practices positively influence performance, their impact on efficiency is shaped by a firm's financial health and strategic approach. The findings offer valuable insights for enhancing sustainable performance and resource allocation in high-tech industries.

KEYWORDS: Operating Efficiency, AI-Driven Technology Companies, Data Envelopment Analysis (DEA), ESG Practices

1. INTRODUCTION

1.1 Background

In recent years, global focus on sustainability and ethical practices has brought Environmental, Social, and Governance (ESG) factors to the forefront of corporate strategy. ESG criteria have become key indicators of a company's long-term viability and investment value. At the same time, artificial intelligence (AI) is transforming industries. Tesla's application of AI in autonomous driving—such as automatic braking and lane-keeping—demonstrates how AI can enhance safety, energy efficiency, and performance. Industries such as healthcare, finance, and manufacturing are also rapidly adopting AI to boost productivity and maintain competitiveness.

With respect to operations in the electronics industry, Taiwan stands out as a global leader in AI adoption, particularly in its technology and semiconductor sectors. Taiwanese companies are leveraging AI to improve efficiency and sustain their competitive edge in the global market. As AI technologies continue to evolve, firms in Taiwan are well-positioned to deliver innovative and adaptive solutions. Meanwhile, ESG has shifted from a compliance obligation to a strategic imperative. According to Friede, Busch, and Bassen (2015), most studies report a positive or neutral relationship between ESG performance and financial outcomes, further emphasizing ESG's growing importance.

Consequently, AI-driven companies in Taiwan are increasingly integrating ESG principles into their core business strategies. Firms with higher ESG scores tend to perform better financially, as evidenced by data from the Taiwan Economic Journal (TEJ). ESG practices not only attract investment but also enhance corporate reputation. Supporting this view, Liang and Renneboog (2020) and Giese et al. (2019) demonstrate that strong ESG performance contributes to operational efficiency, long-term profitability, and more informed investment decisions.

In summary, ESG is gaining momentum in Taiwan through both market expectations and regulatory frameworks. Publicly listed firms are now evaluated based on their ESG performance, directly influencing their market value. For AI-driven companies, aligning innovation with sustainability has become a key challenge and opportunity. A notable example is the collaboration between NVIDIA and Taiwan Semiconductor Manufacturing Company (TSMC), which reflects both technological synergy and ESG commitment. Therefore, this study aims to evaluate the efficiency of Taiwan's AI-based technology companies through the lens of ESG performance.

1.2 Motivation and Purpose

Amid growing global emphasis on sustainability, ESG factors have become key drivers of corporate performance. This study examines how ESG practices influence the efficiency of AI-driven technology companies in Taiwan, a sector known for innovation and rapid AI adoption. Evidence from the Taiwan Economic Journal (TEJ) indicates a positive link between ESG scores and financial performance, highlighting the strategic relevance of ESG integration.

Building on prior studies, such as Chen, Hung, and Wang (2017), which associate higher firm efficiency with better CSR and ESG integration, this research applies Data Envelopment Analysis (DEA) to assess operational efficiency and identify key ESG contributors.

Given increasing stakeholder and regulatory pressure, understanding how ESG practices are embedded in corporate strategies is both timely and essential. The findings aim to offer practical insights for enhancing ESG-driven efficiency, contributing to both academic literature and decision-making among investors, policymakers, and corporate leaders.

Based on the discussion above, the main objectives of this study are as described: (1) to evaluate the efficiency of AI-driven technology companies in Taiwan using DEA, with a focus on ESG practices, (2) to conduct a comparative analysis of these companies based on ESG-related efficiency performance, and (3) to provide practical recommendations for enhancing ESG integration in AI-driven technology firms in Taiwan.

2. LITERATURE REVIEW

2.1 Literature Review on Environmental, Social, and Governance (ESG)

When evaluating a company's value, both operational performance and its social responsibilities are increasingly considered. This idea relates to Corporate Social Responsibility (CSR), first introduced by Bowen in 1953, who argued that businesses should align with societal values beyond just making profits. More recent studies, such as Goffi et al. (2022), confirm that strong CSR efforts can improve overall business performance. Nevertheless, since the 1990s, rising environmental awareness has led to the integration of sustainable development into CSR, evolving into the Environmental, Social, and Governance (ESG) framework, first proposed by the United Nations Global Compact in 2004. Jun (2023) notes that while CSR and ESG are often used interchangeably in the literature, they are distinct concepts and should be differentiated.

In Taiwan, research on ESG practices and outcomes has been increasing. For instance, Lin and Lin (2022) found that financial holding companies listed in ESG rankings had significantly higher stock prices than those not listed. Huang (2022) showed that environmental performance indirectly affects ROE and ROA through governance performance, indicating that investing in environmental CSR (ECSR) can benefit corporate financial performance. Furthermore, Kao (2023) evaluated the operational performance of Taiwan's industrial parks from an ESG perspective and found that the New Taipei Industrial Park performed best in ESG terms.

2.2 Literature Review on Artificial Intelligence (AI) Development and Applications

AI-driven technologies enable real-time analysis of vast data to conserve energy, optimize resources, and improve predictive maintenance, reducing material and energy waste while enhancing manufacturing efficiency—especially in precision-dependent industries like Taiwan's semiconductor sector. Sætra (2022) highlights that AI-based environmental tracking and control systems can help businesses meet rising expectations on climate change and resource use. Additionally, AI can analyze employee data to design tailored training programs, improving skills and satisfaction. Saxena et al. (2023) note that this supports social sustainability, as a healthy, skilled workforce underpins firms' long-term growth and stability.

AI has transformed key sectors such as manufacturing, healthcare, and finance by enabling automation, predictive analytics, and better decision-making (Marr, 2020; Esteva et al., 2017; Goodell & Goutte, 2021). In Taiwan's semiconductor industry, where even minor process deviations can lead to significant losses, AI plays a critical role in predictive maintenance, defect detection, and process optimization. Studies show AI-based systems proactively identify equipment anomalies, preventing failures and minimizing production losses (Hsua et al., 2012), while major investments by firms like TSMC further strengthen Taiwan's global leadership (Chu et al., 2020).

Beyond efficiency, AI supports Taiwan's sustainability goals. Wu (2022) notes that AI-driven systems in electronics and manufacturing help optimize resources, cut waste, and align operations with ESG objectives, even fostering international collaboration on sustainable solutions. In healthcare, AI-powered automation and digital transformation—such as robotic process automation—reduce administrative burdens, improve care quality, and support leaner, more sustainable healthcare models (Huang et al., 2024).

2.3 Literature Review on Operating Performance Using the DEA Method

Data Envelopment Analysis (DEA) has become an important tool for assessing corporate performance, especially as companies are increasingly evaluated on both financial outcomes and ESG criteria. Studies such as Cheng et al. (2023) and Kao (2023) show

that firms with higher ESG engagement—particularly in the technology sector—tend to utilize resources more efficiently, achieve stronger financial results, and gain brand value and stakeholder trust.

DEA's strength lies in its ability to handle multiple inputs and outputs, identifying which firms operate on the efficiency frontier and which lag behind. Research by Tsaih, Chiang, and Yen (2021) and Hsiao et al. (2019) highlights how DEA can pinpoint underperforming companies and indicate areas for improvement, using approaches like CRS models to provide a comprehensive view of operational efficiency.

Applications of DEA span numerous industries, including technology, healthcare, and semiconductors. Recent studies, such as He, Liu, and Lin (2024), examine how Taiwanese semiconductor firms leverage intellectual capital, while Chen, Lin, and Yu (2022) analyze resource utilization across organizational units like R&D, production, and marketing. These findings underscore DEA's value in offering a holistic perspective on efficiency—particularly for AI-driven technology firms in Taiwan that must innovate while aligning with global ESG standards.

3. METHODOLOGY

3.1 Research Sample and Data Sources

This study examines the operational performance of companies in Taiwan's AI and digital technology industries by analyzing a sample of publicly traded and listed on the Taiwan Stock Exchange (TWSE) or OTC firms. Quarterly data from Q4 2019 to Q3 2024 (16 quarters) are drawn from TEJ database. This period was selected to capture the impact of the COVID-19 pandemic, the surge in remote work demand, and the subsequent acceleration of AI adoption—factors that significantly influenced the performance of Taiwan's AI-related companies.

This study focuses on Taiwanese suppliers collaborating with NVIDIA, as identified from Jensen Huang's keynote at Computex 2024. These suppliers may specialize in niche operations within a single stage of the industry value chain—upstream, midstream, or downstream—while others engage in diversified activities across multiple stages. In addition, non-electronics suppliers and firms lacking complete data for the sample period were excluded from the analysis. The final sample comprises 40 companies, categorized by industry type as shown in Table 1. The largest group is the computer and peripheral equipment sector, reflecting Taiwan's global leadership in hardware production and the integration of AI into design and manufacturing.

Table 1. Summary of Sample Information by Industrial Category

Category	Industry type	No. of firms
1	Computer and Peripheral Equipment industry	24
2	Semiconductor industry	5
3	Electronic Parts and Components industry	2
4	Other Electronic	3
5	Electronic Products Distribution	1
6	Optoelectronic	3
7	Communications and Internet	1
8	Biotechnology and Medical Care	1
Total		40

Source: Compiled by This Study

3.2 Research Methodology and Research Variables

Data Envelopment Analysis (DEA) is applied to evaluate the relative efficiency of the 40 AI-driven technology companies in this study. DEA assesses decision-making units (DMUs) with multiple inputs and outputs by projecting them into a geometric space to form an efficiency frontier. Of its two main models, the CCR model (Charnes, Cooper, & Rhodes, 1978) is selected for its assumption of constant returns to scale (CRS) and its suitability for comparing overall resource utilization under consistent conditions.

The CCR model generates efficiency scores that serve as the basis for empirical analysis. These scores are used to compare operational efficiency across different quarters and to explore variations between TWSE-listed and over-the-counter companies, across industry classifications, and among firms positioned at different stages of the supply chain (upstream, midstream, and downstream).

To select input and output variables, this study reviewed prior literature (e.g., Chen & Chen, 2007; Ben & Wang, 2011; Lu et al., 2013; Kauo et al., 2014; Wu et al., 2019; Chen et al., 2021; Lin & Ding, 2021). The review identified asset-related variables, cost- and expense-related variables, and R&D expenditures as the most common inputs, while revenue- and profit-related variables

were the primary outputs. These variables were adopted to capture both financial performance and innovation, thereby providing a holistic assessment of firms' operational efficiency.

4. EMPIRICAL RESULTS AND ANALYSES

4.1 Samples and Descriptive Statistics

Table 2 summarizes the variables used in the DEA model: total operating expenses (I1), R&D expenses (I2), and operating revenue (O1). The data reflect differences in company scale. Pearson correlation analysis (Table 3) shows significant positive relationships among inputs and output at the 0.01 level, supporting the suitability of these variables for DEA.

Table 2. Descriptive Statistics of Input and Output Variables

Unit: Million NT Dollars

Variable	N	Minimum	Maximum	Mean	Std. Deviation
I1	640	31,985	79,078,904	6,823,183	$1.322 \cdot 10^7$
I2	640	4,593	52,783,826	3,811,589	8,566,939.843
O1	640	61,540	2,009,011,936	$1.07 \cdot 10^8$	$2.675 \cdot 10^8$

Table 3. Correlations Analysis of Input and Output Variables

		I1	I2	O1
I1	Pearson Corr.	1	0.972	0.802
	Sig. (2-tailed)		0.000^{***}	0.000^{***}
I2	Pearson Corr.	0.972	1	0.686
	Sig. (2-tailed)	0.000^{***}		0.000^{***}
O1	Pearson Corr.	0.802	0.686	1
	Sig. (2-tailed)	0.000^{***}	0.000^{***}	

Note：*** indicates that correlation is significant at the 0.01 level (2-tailed).

4.2 Empirical Results: DEA Efficiency Scores

This study uses open-source DEA software, where efficiency scores range from 0 to 1. Higher values indicate better relative efficiency. As shown in Table 4, the low standard deviation suggests minimal variation in efficiency across enterprises. However, average quarterly efficiency remains below 0.5, indicating generally poor performance. The highest value appears in Q2 but still falls short of optimal efficiency. One-way ANOVA results (Table 5) show no significant differences in performance across quarters.

Table 4. Descriptive Statistics of DEA Efficiency Scores

	Number	Minimum	Maximum	Mean	Std. Deviation
Total	640	.02162	1	.22821	.21608
Quarter 1	160	.02162	1	.22197	.20981
Quarter 2	160	.03361	.90732	.22316	.20482
Quarter 3	160	.03465	1	.23013	.21920
Quarter 4	160	.03610	1	.23759	.23123

Table 5. Quarterly Differences Comparison: One-Way ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.025	3	0.008	0.178	0.912
Within Groups	29.810	636	0.047		
Total	29.835	639			

To compare performance, the sample was divided into ESG-ETF constituents (16 firms) and non-constituents (24 firms), as shown in Table 6. Firms in the ESG-ETF group show higher average efficiency, suggesting stronger ESG implementation and consistency. An independent samples t-test (Table 7) confirms the difference is statistically significant (mean difference = 0.0914), with Levene's test supporting equal variances. These findings imply that ESG performance differences may stem from industry factors, corporate sustainability strategies, or regulatory influences.

Table 6. Group Statistics: ESG-ETF Index Constituents

Group	N	Mean	Std. Deviation	Std. Error Mean
1- ESG-ETF Index Constituents	256	.2831	.18361	.01148
2- Not ESG-ETF Index Constituents	384	.1917	.22826	.01165

Table 7. Independent-Samples t Test: ESG-ETF Index Constituents

	F	Sig.	t	Sig. (2-tailed)	Mean Difference
Equal variances assumed	.464	.496	5.355	.000***	.0914

Note：*** indicates that correlation is significant at the 0.01 level (2-tailed).

The study also conducted an independent samples t-test to compare diversification and niche strategies among AI tech firms in Taiwan. Firms with a niche strategy had a mean score of 0.2208, while those with a diversification strategy scored slightly higher at 0.2505 (Table 8). Levene's test indicated unequal variances ($F = 13.116$, $p < 0.001$), so Welch's t-test was applied. The result ($t = -1.816$, $p = 0.070$) suggests a slight, non-significant advantage for diversification.

Table 8. Group Statistics: Niche or Diversification in Operation

Group	N	Mean	Std. Deviation	Std. Error
1-Niche	480	.2208	.23202	.01059
2-Diversification	160	.2505	.15743	.01244

Table 9. Independent-Samples t Test: Niche or Diversification in Operation

	F	Sig.	t	Sig.(2-tailed)	Mean Difference
Equal variances not assumed	13.116	.000***	-1.816	.070*	-.02967

Note：* indicates that correlation is significant at the 0.10 level (2-tailed).

Tables 10 and 11 show that firms in the Computer and Peripheral Equipment sector outperformed those in other tech sectors. Levene's test confirmed unequal variances ($F = 22.576$, $p < 0.001$), and Welch's t-test showed a significant difference ($t = 3.688$, $p < 0.001$; mean difference = 0.0621). These results suggest that industry-specific factors significantly affect performance, highlighting the need for sector-based analysis of AI firms.

Table 10. Group Statistics: Two Different Electronic Industry Groups

Group	N	Mean	Std. Deviation	Std. Error Mean
1- Computer & Peripheral Equipment	384	.25306	.22425	.01144
2-Others	256	.19093	.19783	.01236

Table 11. Independent-Samples t Test: Two Different Electronic Industry Groups

	F	Sig.	t	Sig. (2-tailed)	Mean Difference
Equal variances not assumed	22.576	.000***	3.688	.000***	.06212

Note：*** indicates that correlation is significant at the 0.01 level (2-tailed).

Tables 12 and 13 compare TWSE-listed (Group 1) and OTC-listed (Group 2) companies. Group 1 ($n = 512$) had a higher mean score (0.2624) than Group 2 ($n = 128$; mean = 0.0914). Levene's test confirmed unequal variances ($F = 169.956$, $p < 0.001$), and the large mean gap suggests TWSE-listed firms significantly outperform OTC-listed firms in financial and ESG metrics.

Table 12. Group Statistics: Types of Listing in Exchange or OTC

Group	N	Mean	Std. Deviation	Std. Error Mean
1- Listed in Exchange	512	.26240	.22880	.01011
2- Listed in OTC	128	.09141	.02633	.00232

Table 13. Independent-Samples t Test: Types of Listing in Exchange or OTC

	F	Sig.	t	Sig. (2-tailed)	Mean Difference
Equal variances not assumed	169.956	.000***	16.480	.000***	.17099

Note：*** indicates that correlation is significant at the 0.01 level (2-tailed).

4.3 Results: Influential Factors on DEA Efficiency Scores

Stepwise regression identified three key predictors: gross margin ratio (X1), total assets growth rate (X2), and cash flow ratio (X3). Two additional variables—chain structure (X4) and listing status (X5)—were also included. The model (Tables 14-16) shows strong fit ($R = 0.704$, $R^2 = 0.496$, Adjusted $R^2 = 0.492$), indicating that 49.6% of efficiency variation is explained. The F-statistic (124.686, $p < 0.001$) confirms overall model significance. VIF values (Table 19) are all near 1, suggesting no serious multicollinearity. Overall, the regression model is statistically sound and suitable for this study.

Table 14. Model Summary

R	R2	Adjusted-R^2	Std. Error of the Estimate
.704	.496	.492	.15403

Table15. Goodness of Fit Test: ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	14.792	5	2.958	124.686	.000***
Residual	15.043	634	.024		
Total	29.835	639			

Note：*** indicates that correlation is significant at the 0.01 level (2-tailed).

Table 16. Regression Model Result

Variable	T	Sig.	VIF
(Constant)	20.547	.000***	
X1-Gross Margin Ratio	-21.549	.000***	1.288
X2-Total Assets Growth Rate	2.931	.004***	1.019
X3-Cash Flow Ratio	3.532	.000***	1.235
X4-Chain Stage	-3.652	.000***	1.076
X5-Listing Type	-6.519	.000***	1.089

Note：*** indicates that correlation is significant at the 0.01 level (2-tailed).

5. CONCLUSIONS AND SUGGESTIONS

5.1. Conclusions

This study examines 40 AI technology firms from Q4 2019 to Q3 2024 using financial and ESG data from the Taiwan Economic Journal (TEJ). Data Envelopment Analysis (DEA) reveals how ESG factors impact firm efficiency. Regression analysis identifies gross margin ratio (X1), total assets growth rate (X2), and cash flow ratio (X3) as key drivers of efficiency. External factors such as chain structure (X4) and listing status (X5) also influence performance.

Results show that financial and structural factors play a stronger role in enhancing efficiency than ESG factors alone. Firms with higher gross margins, steady asset growth, and strong cash flow perform better. Single-stage production firms and those listed on the TWSE show higher efficiency. ESG integration supports performance but is most effective when aligned with strong financial fundamentals and market conditions. Firms should embed ESG into strategy, supported by robust reporting and investment in sustainable practices.

5.2 Suggestions

Firms should adopt advanced financial analytics and AI-based forecasting to improve cash flow planning and avoid liquidity issues. Effective cash flow management enhances resource allocation and operational flexibility.

While ESG factors may not yield immediate efficiency gains, integrating them with financial goals supports long-term value creation. ESG adoption improves reputation, attracts responsible investors, and builds stakeholder trust. Policymakers should provide clear guidelines and incentives to encourage ESG integration in AI firms, while enhancing transparency and standardized reporting to boost investor confidence.

Efficiency is also influenced by supply chain structure. Firms operating in a single production stage tend to be more efficient. Strategic alignment or partnerships in the supply chain can further reduce inefficiencies and improve performance.

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