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Are Korean AI Firms Really Growing Sustainably? Operational Efficiency by Period, Firm Age, Firm Size, and Region

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Abstract

The sustainable growth of the AI industry depends not only on market expansion and technological advancement but also on whether AI supplier firms can efficiently transform their resource investments into stable economic outcomes. This study examines the operational efficiency of Korean AI supplier firms from the perspective of resource-efficient and sustainable growth and investigates differences across periods, firm age, firm size, and region. Using financial data from 95 firms over 2017–2025, we constructed 855 firm-year decision-making units and applied input-oriented data envelopment analysis under CRS and VRS. Nonparametric tests were subsequently used to compare efficiency across firm groups. The results show that both CRS and VRS efficiency declined over time, with the lowest efficiency observed during 2023–2025 despite the rapid diffusion of generative AI. Firms aged 19–25 years exhibited relatively higher efficiency than younger and older firms. Firm-size comparisons revealed contrasting patterns: SMEs showed higher CRS efficiency, whereas mid-sized enterprises exhibited higher VRS efficiency. Regional differences were significant for CRS efficiency but not for VRS efficiency, with firms outside Seoul and Gyeonggi showing relatively higher CRS efficiency. From a sustainability perspective, these findings indicate that rapid industry expansion based on increasing investments does not automatically lead to efficient or sustainable firm-level growth. The study therefore highlights the importance of resource-efficient operations, appropriate scale, and sustainable revenue structures in promoting the long-term economic sustainability of AI supplier firms and the AI industry.

Keywords: artificial intelligence; AI supplier firms; sustainable growth; data envelopment analysis; operational efficiency; regional differences

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Academic Editor: Miltiadis (Miltos) Alamaniotis

Received: 27 August 2026
Revised: 30 September 2026
Accepted: 6 October 2026
Published: 10 October 2026

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1. Introduction

Artificial intelligence (AI) is no longer confined to specific industries or specialized technological domains; rather, it has emerged as a general-purpose technology that is transforming firms' production processes, decision-making, customer management, product development, and value-creation structures. Through a wide range of functions, including data analytics, prediction, automation, natural language processing, image recognition, and decision support, AI can enhance the efficiency of business activities and facilitate the development of new business models [1]. In particular, AI capability should be understood not simply as the possession of specific technologies or software, but as an organizational

capability to integrate data, technological infrastructure, human capital, and organizational intangible resources and convert them into business outcomes [2]. Similarly, the outcomes of AI-enabled digital transformation depend less on the mere adoption of technology than on how effectively AI is integrated with a firm's strategy, organizational structure, and business processes [3].

As the application of AI continues to expand across industries, AI supplier firms that directly develop AI technologies or provide AI-based products, services, and solutions are becoming increasingly important. However, the substantial growth potential of the AI industry does not necessarily translate into superior business performance at the individual firm level. AI firms require continuous investment in areas such as algorithm development, data acquisition and preprocessing, model training, cloud infrastructure, and highly skilled technical personnel. Although investments in research and development and intangible assets may enhance firm value over the long term, they may also appear as higher costs and lower profitability in short-term accounting performance [4]. Moreover, general-purpose technologies such as AI are often characterized by a time lag between technological investment and realized productivity gains, with substantial economic benefits emerging only after complementary investments and organizational changes have accumulated [5].

Existing studies have primarily examined the relationship between AI capabilities and firm performance among firms that adopt and utilize AI technologies [1,2,6]. In comparison, relatively limited empirical attention has been paid to how efficiently firms that directly develop and supply AI technologies convert their resource inputs into sales and profits. Furthermore, insufficient research has examined how the efficiency of AI supplier firms is associated not only with changes in the industrial environment, such as the COVID-19 pandemic and the rapid diffusion of generative AI, but also with firm characteristics such as age, size, and geographic location.

Accordingly, this study analyzes the operational efficiency of Korean AI supplier firms from 2017 to 2025 using data envelopment analysis (DEA). Specifically, first, it examines differences in efficiency across three periods: the pre-COVID-19 period (2017–2019), the COVID-19 period (2020–2022), and the post-COVID-19 and generative AI diffusion period (2023–2025). Second, firms are classified into three age groups—18 years or less, 19–25 years, and 26 years or more—and their efficiency levels are compared. Third, the study examines differences in efficiency between small and medium-sized enterprises (SMEs) and mid-sized enterprises. Fourth, it investigates efficiency differences among firms located in Seoul, Gyeonggi, and other regions.

This study contributes to the existing literature in three respects. First, by examining the performance of firms that supply AI technologies rather than firms that merely adopt or use them, this study extends empirical understanding of the supply side of the AI industry. Second, rather than assessing firm performance solely in terms of the absolute levels of sales or profits, this study evaluates performance from an efficiency perspective by examining how effectively resource inputs are transformed into business outcomes. In doing so, it provides a more critical assessment of the prevailing narrative surrounding the rapid growth of the AI industry. From a sustainability perspective, this study approaches sustainability from an economic and resource-utilization perspective by examining whether the rapid expansion of the AI industry is accompanied by efficient and sustainable firm-level performance. Third, by jointly comparing efficiency under constant returns to scale (CRS) and variable returns to scale (VRS), this study identifies whether efficiency differences across periods, firm age groups, firm sizes, and regions manifest differently in overall technical efficiency and pure technical efficiency. Through these analyses, the study provides firm-level empirical evidence addressing a fundamental question: As the AI industry continues to grow, are AI supplier firms themselves actually becoming more efficient?

2. Theoretical Background

2.1. Performance Analysis of AI Supplier Firms

Artificial intelligence has been widely discussed as a core technology that transforms firms' operational processes and value-creation structures through various functions, including data analytics, prediction, automation, natural language processing, image recognition, and decision support. Enholm, Papagiannidis [1] explained that AI can generate diverse forms of business value, such as cost reduction, revenue generation, process automation, and improved decision-making. However, such outcomes do not arise merely from possessing or adopting AI technologies; rather, they depend on how effectively firms integrate these technologies into their organizations and business processes. Mikalef and Gupta [2] similarly conceptualized AI capability as an organizational capability that combines technological resources, human resources, and organizational intangible resources, and suggested that AI capability can influence organizational creativity and firm performance. Accordingly, the business performance of AI should be understood not in terms of the level of individual technologies alone, but from the perspective of a firm's ability to combine diverse resources and transform them into actual business outcomes.

When evaluating the performance of AI supplier firms, comparisons based solely on absolute financial outcomes, such as sales or net income, have important limitations. AI firms require not only tangible assets, such as servers and research facilities, but also substantial intangible assets, including software, algorithms, databases, and intellectual property. They also rely heavily on highly skilled human capital, such as specialized developers and data scientists. Corrado, Hulten [7] argued that intangible investments, including research and development, software, and organizational capital, function as important factors of production in the growth of modern firms. Mikalef and Gupta [2] likewise identified technological infrastructure, human resources, and organizational intangible resources as key components of AI capability. Therefore, to evaluate the performance of AI supplier firms more accurately, it is necessary to examine how efficiently investments in tangible assets, intangible assets, and human capital are converted into actual sales and profits.

In particular, AI firms are likely to experience a time lag between technological investment and financial performance. Lev and Sougiannis [4] explained that although R&D expenditures can generate long-term economic value, they are treated as expenses in short-term accounting statements and may therefore reduce current earnings. Brynjolfsson and Hitt [8] also argued that for information technology investments to translate into firm performance, complementary investments, such as organizational change and improvements in business processes, are required in addition to the technological assets themselves. Brynjolfsson, Rock [5] explained this phenomenon through the productivity J-curve, arguing that productivity may initially remain low following the adoption of general-purpose technologies because of complementary intangible investments, with performance improvements becoming visible only after a certain period. Accordingly, even if investment in and market demand for AI continue to expand, it cannot be assumed that the input–output efficiency of individual AI supplier firms will increase simultaneously.

Existing AI-related studies have primarily focused on the relationship between AI capabilities and firm performance among firms that adopt or utilize AI technologies [1,2,6]. In contrast, relatively limited attention has been paid to how effectively firms that directly develop and supply AI technologies convert tangible assets, intangible assets, and human resources into market performance and profitability. In particular, because the overall expansion of the AI industry may not necessarily coincide with efficiency improvements at the individual AI supplier firm level, these two phenomena need to be distinguished and analyzed separately.

2.2. Comparisons Across Groups of AI Supplier Firms

The efficiency of AI supplier firms may not be uniform across firms but may vary according to the industrial environment in which they operate and their firm-specific characteristics. Even when firms possess similar levels of technology or resources, the process through which those resources are converted into performance may differ depending on market demand, technological change, organizational experience, firm size, and geographic location. Therefore, understanding the efficiency of AI supplier firms requires not only an examination of their overall efficiency levels but also comparisons among groups of firms operating under different conditions.

First, the efficiency of AI supplier firms may vary across different environmental periods. The COVID-19 pandemic accelerated firms' digital transformation by increasing the need for remote work, online transactions, automation, and data-driven decision-making [9]. Papadopoulos, Baltas [10] showed that SMEs used digital technologies to respond to supply-chain disruptions and operational risks during the pandemic, while Drydakis [11] suggested that AI applications could reduce business risks and strengthen firms' dynamic capabilities. Meanwhile, although the diffusion of generative AI after the COVID-19 pandemic further expanded demand for AI [12,13], the proliferation of global general-purpose models and API-based services may also have intensified competition among AI supplier firms. Therefore, comparing firm efficiency across the pre-COVID-19, COVID-19, and post-COVID-19 periods is necessary to determine whether the expansion of the AI market has translated into improvements in the resource utilization efficiency of AI supplier firms.

Second, firm age reflects organizational experience, organizational learning, and the ability to adapt to technological change. Jovanovic [14] explained that firms learn about their own efficiency as they operate in the market, while firms with lower efficiency may be eliminated through competitive selection. From the perspective of Stinchcombe [15] liability of newness, relatively young firms may face difficulties because they lack experience, established organizational systems, and external legitimacy. However, greater firm age does not necessarily imply greater efficiency. Older firms may become constrained by established organizational structures and routines, making it difficult to respond rapidly to technological change Hannan and Freeman [16]. Thus, in rapidly evolving industries such as AI, the relationship between firm age and efficiency may be characterized by differences across stages of organizational development rather than by a simple linear pattern.

Third, firm size may also be associated with the efficiency of AI supplier firms. Taymaz [17] suggested that technical efficiency and returns to scale may differ according to firm size, while Rapposelli, Birindelli [18] showed that larger firms may achieve higher efficiency because of their relatively stronger access to financial resources and other strategic resources. However, increases in firm size may also generate inefficiencies associated with more complex managerial structures and higher costs of information transmission and decision-making [19]. Although SMEs tend to face greater resource constraints, they may respond more effectively to changing technological environments through relatively simple organizational structures, faster decision-making, and more flexible resource allocation [20]. Schiersch [21] further suggested that the relationship between firm size and efficiency may be nonlinear rather than simply linear, with both smaller and larger firms exhibiting relatively high efficiency. Accordingly, this study compares the efficiency of small and medium-sized AI supplier firms with that of mid-sized AI supplier firms.

Fourth, the efficiency of AI supplier firms may also differ depending on their regional environment. Audretsch and Feldman [22] showed that innovation activities in knowledge-intensive industries tend to cluster geographically and explained that knowledge spillovers and access to specialized human capital are associated with firms' innovation activities.

Porter [23] likewise argued that industrial clusters can promote productivity and innovation through interfirm competition and cooperation, supplier networks, and access to specialized labor. However, regions with high concentrations of firms and skilled workers, such as Seoul, also tend to impose higher labor and operating costs. Therefore, the benefits of geographic agglomeration do not necessarily translate into greater input–output efficiency. Accordingly, this study compares firms located in Seoul, Gyeonggi, and other regions to examine whether the regional concentration of the AI industry is associated with actual firm-level efficiency.

3. Research Method

3.1. Sample and Data

The sample for this study was drawn from the 2026 AI Voucher Support Program supplier pool administered by the National IT Industry Promotion Agency (NIPA), which consisted of 1428 registered AI supplier firms. These firms were matched with financial information available through VALUEsearch, a Korean corporate financial database. Among the 1428 firms, 136 firms subject to external audit and for which financial information could be matched were initially identified. Of these, 41 firms were excluded because complete financial data were not available for one or more years during the 2017–2025 period, resulting in a final sample of 95 firms.

The 2026 AI Voucher supplier pool was used to identify firms with verified AI supply capabilities. Firms applying for registration are required to possess their own AI solutions and undergo eligibility review and expert verification of those solutions. However, information on the year in which each firm first entered the supplier pool is not available. Therefore, this study does not assume that all sampled firms were formally registered as AI Voucher suppliers throughout the entire 2017–2025 period. Rather, the longitudinal financial data are used to examine the firm-level operational trajectories of firms identified as AI suppliers in the 2026 supplier pool.

The use of firms with complete observations over the entire nine-year period was consistent with the purpose of this study, which is to examine how the operational efficiency of AI supplier firms changed over a relatively long period using a common set of firms. Accordingly, a balanced panel was constructed to ensure comparability across the three study periods. This sampling criterion necessarily excludes firms established after 2017 as well as firms without continuous financial records during the study period.

Through this selection procedure, a total of 855 firm-year decision-making units (DMUs) were constructed by combining nine years of data, from 2017 to 2025, for 95 firms. Each firm-year observation was treated as a distinct DMU, such that the same firm could constitute different DMUs across years as its input–output structure changed over time. This treatment of repeated firm-year observations as separate DMUs has been commonly adopted in longitudinal DEA studies [24–27]. The firm-year observations were organized in a pooled framework. Rather than constructing a separate efficiency frontier for each year, all observations over the 2017–2025 period were evaluated against a common frontier. Using separate frontiers for different years would result in different reference benchmarks, which may limit direct comparisons of efficiency across periods. Previous longitudinal DEA studies have similarly pooled multi-year observations and evaluated them against a common or global frontier for intertemporal comparisons [25–27]. Accordingly, the DEA efficiency scores estimated in this study should not be interpreted as relative efficiency within a particular year. Instead, they represent relative efficiency based on a common benchmark that compares the input–output structures of AI supplier firms across the entire nine-year study period.

3.2. Variables

In DEA, the selection of input and output variables should appropriately reflect the resource structure of the firms under analysis and the process through which those resources are transformed into performance. This study conceptualizes AI supplier firms as technology-intensive firms that combine physical resources, knowledge-based resources, and human capital to develop AI products and services and transform them into market outcomes. Based on this perspective, three input variables were selected. Similarly, Mishra, Ewing [28], in examining the relationship between firms' AI focus and operating efficiency, employed broad firm-level measures including tangible investment, intangible investment, employment, sales, and net income-based performance measures.

First, tangible assets were included as an input variable representing the physical infrastructure used by AI firms to develop and operate their products and services. The business activities of AI supplier firms require physical infrastructure that supports technological development and service provision, including computing equipment, servers, and research and office facilities [2].

Second, intangible assets were used to capture the knowledge-based resources of AI supplier firms, including software, algorithms, data, intellectual property, and R&D-related outcomes. Corrado, Hulten [7] identified intangible investments, such as software, R&D, and organizational capital, as important factors of production underlying the growth and productivity of modern firms. Intangible assets are particularly relevant to AI firms because the industry relies more heavily on knowledge-based assets, such as algorithms, software, and data, than on physical facilities. Accordingly, intangible assets constitute an important input in evaluating the resource utilization of AI supplier firms.

Third, labor cost was included as an input variable representing human capital investment. Human resources play a particularly important role in value creation among AI supplier firms because the development of AI products and services depends heavily on AI researchers, software developers, data scientists, and other highly skilled professionals [2,6].

The output variables were sales and net income. Sales represent a key indicator of market performance by reflecting the extent to which the products, services, and solutions developed by AI firms are translated into actual customer demand and market transactions. Wamba-Taguimdje, Fosso Wamba [3] emphasized that the business performance of AI-based technologies depends not merely on technology adoption itself but on the extent to which such technologies generate actual business value. From this perspective, sales can capture the extent to which the technologies and services provided by AI supplier firms are converted into economic value in the market.

Net income, in contrast, represents the ultimate profitability retained by a firm after accounting for various costs, including R&D expenditures, labor costs, and infrastructure expenses. As noted by Lev and Sougiannis [4], increases in sales among technology-intensive firms may not necessarily coincide with short-term increases in profits because of substantial R&D investment. Thus, evaluating firm performance requires consideration of both market performance and final profitability. Accordingly, this study employs sales and net income simultaneously as output variables to capture both the market performance and profitability of AI supplier firms. All financial variables were measured in nominal KRW, and no separate adjustment for price changes was applied because the analysis focuses on the relative input–output efficiency of firms against a common benchmark rather than changes in the absolute levels of financial variables.

Some AI supplier firms may report negative net income because of growth-related expenditures and investments in R&D. To satisfy the non-negativity requirement of DEA, variables containing negative values were shifted upward by adding a common constant to all observations such that the minimum value of the variable became 1. Although such

a transformation should be applied cautiously in the CCR model because it is not strictly translation invariant, it has nevertheless been adopted in previous empirical studies using CCR-CRS models to accommodate variables containing negative values [29,30]. As the descriptive statistics in Table 1 are reported in million KRW and rounded to two decimal places, this minimum value is displayed as 0.00 in the table.

Table 1. Descriptive statistics of variables.

Groups	Variable	N	Mean	Std. Div.	Min.	Max.
Input	Tangible assets	855	6361.81	10,913.97	0.62	72,509.38
	Intangible assets	855	1921.94	4296.95	0.00	41,199.59
	Labor cost	855	5902.25	13,798.21	22.74	116,995.00
Output	Sales	855	38,393.47	64,319.52	38.18	475,914.00
	Net income	855	114,604.18	10,063.78	0.00	182,884.00

Unit: million KRW. Note: Net income represents the shifted values used in the DEA. A common constant was added to all net income observations so that the minimum transformed value was KRW 1.

3.3. Model of Data Envelopment Analysis

To examine the relative efficiency with which tangible assets, intangible assets, and labor costs are transformed into sales and net income, this study employs DEA. DEA is a nonparametric efficiency measurement technique that simultaneously accommodates multiple inputs and multiple outputs and constructs an efficient frontier based on observed data without requiring the specification of a particular functional form for the production function [31]. Banker, Charnes [32] extended the DEA framework by allowing variable returns to scale, thereby enabling a distinction between overall technical efficiency and pure technical efficiency after controlling for scale effects. Wang, Gopal [33] employed DEA to evaluate the efficiency of IT investment in generating firm performance, while Shao and Lin [34] examined the technical efficiency of information technology investment, demonstrating the usefulness of DEA for evaluating resource utilization in technology-intensive firms. DEA is therefore well suited to assessing the resource utilization efficiency of AI supplier firms that differ in firm size and business model.

This study applies an input-oriented DEA model to examine the extent to which AI supplier firms could reduce inputs, including tangible assets, intangible assets, and labor costs, while maintaining their existing levels of sales and net income. In the short term, AI supplier firms may have limited direct control over output-side factors, such as market demand or the size of customer contracts. In contrast, the scale and allocation of internal resources, including tangible assets, intangible assets, and labor costs, are relatively more subject to managerial control. An input-oriented DEA model was therefore considered appropriate for evaluating the operational efficiency of AI supplier firms.

To provide a more detailed assessment of efficiency, this study applies both the CRS and VRS models. The CRS model proposed by Charnes, Cooper [31] measures overall technical efficiency based on the assumption that all firms operate at an optimal scale. In contrast, the VRS model developed by Banker, Charnes [32] allows for variable returns to scale and therefore measures pure technical efficiency by separating the effect of firm scale. Banker, Charnes [32] demonstrated that this distinction makes it possible to determine whether inefficiency arises primarily from problems in resource management and operations or from operating at a non-optimal scale. This distinction is particularly important when analyzing AI supplier firms of different sizes because firms with similar operational capabilities may exhibit different levels of overall efficiency depending on their scale of operation. Accordingly, both CRS and VRS efficiency scores were estimated in this study.

After estimating operational efficiency using DEA, differences in efficiency were examined according to period, firm age, firm size, and region. For period, firm age, and region, each of which consisted of three or more groups, the Kruskal–Wallis test was first conducted. When statistically significant differences were identified, Mann–Whitney U tests were subsequently performed for post hoc pairwise comparisons. The reported *p*-values for these post hoc pairwise comparisons are unadjusted, and the Mann–Whitney U tests were used as follow-up analyses to identify pairwise differences after the omnibus Kruskal–Wallis test, consistent with approaches used in previous DEA studies [35–37]. Because firm size consisted of only two groups—SMEs and mid-sized enterprises—the Mann–Whitney U test was applied directly.

The study period was divided into three categories: the pre-COVID-19 period (2017–2019), the COVID-19 period (2020–2022), and the post-COVID-19 and generative AI diffusion period (2023–2025). Firm age was calculated as of 2025 and classified into three groups: 18 years or less, 19–25 years, and 26 years or more. The 2025 age classification was consistently applied throughout the analysis. The cutoffs were selected to obtain three approximately balanced groups (33, 28, and 34 firms, respectively), consistent with previous empirical studies that have used age-group classifications to examine firm heterogeneity [38,39]. Firm size was divided into SMEs and mid-sized enterprises, while geographic location was classified into Seoul, Gyeonggi, and other regions.

4. Results

4.1. Operational Efficiency of AI Supplier Firms

Table 2 presents the descriptive statistics for the DEA efficiency scores of the firms included in the analysis. Across the full sample of 855 firm-year observations, the mean CRS efficiency score was 0.24, whereas the mean VRS efficiency score was 0.29, indicating that average efficiency was relatively higher under the VRS specification. By period, the mean CRS efficiency declined from 0.28 in 2017–2019 to 0.22 in 2020–2022 and further to 0.20 in 2023–2025. A similar pattern was observed for VRS efficiency, with corresponding mean values of 0.32, 0.28, and 0.27.

Table 2. Descriptive statistics of CRS and VRS.

		CRS		VRS	
Groups	**N**	**Mean**	**Std. Div.**	**Mean**	**Std. Div.**
‘17–‘19	285	0.28	0.25	0.32	0.26
‘20–‘22	285	0.22	0.22	0.28	0.25
‘23–‘25	285	0.20	0.22	0.27	0.27
18 y or less	297	0.25	0.26	0.29	0.29
19–25 y	252	0.27	0.24	0.31	0.26
26 y or more	306	0.19	0.19	0.27	0.23
SMEs	738	0.24	0.23	0.28	0.25
Mid-sized Enterprises	117	0.21	0.25	0.35	0.30
Seoul	558	0.22	0.23	0.29	0.27
Gyeonggi	198	0.21	0.17	0.25	0.19
Others	99	0.34	0.33	0.37	0.33
Total	855	0.24	0.23	0.29	0.26

Differences were also observed across firm characteristics. In terms of firm age, firms aged 19–25 years exhibited the highest mean efficiency, with CRS and VRS scores of 0.27 and 0.31, respectively, whereas firms aged 26 years or more recorded corresponding scores of 0.19 and 0.27. With respect to firm size, SMEs had a higher mean CRS efficiency score than mid-sized enterprises (0.24 vs. 0.21). In contrast, under the VRS specification, mid-sized enterprises exhibited a higher mean efficiency score than SMEs (0.35 vs. 0.28), indicating different patterns between the CRS and VRS models. By region, firms located in other regions exhibited relatively higher mean efficiency scores, at 0.34 for CRS and 0.37 for VRS, compared with firms located in Seoul and Gyeonggi. Overall, these descriptive statistics suggest that efficiency levels may vary across periods, firm age groups, firm sizes, and regions.

However, these differences in mean values are descriptive and do not necessarily indicate statistically significant differences in efficiency across groups. DEA is a nonparametric method that estimates relative efficiency, and its efficiency scores are bounded between 0 and 1, with observations potentially clustering at the upper bound of 1. Accordingly, the assumption of normality may not be appropriate. Therefore, additional nonparametric tests were conducted to determine whether the group differences observed in the descriptive statistics were statistically significant.

4.2. Differences in Efficiency Across Periods

First, efficiency was compared across the pre-COVID-19, COVID-19, and post-COVID-19 periods. The results of the Kruskal–Wallis test by period are presented in Table 3. The results of the Kruskal–Wallis test indicated statistically significant differences in CRS efficiency across the three periods. The mean ranks were 492.68 for 2017–2019, 418.13 for 2020–2022, and 373.18 for 2023–2025, indicating a consistent downward trend in the relative ranking of CRS efficiency over time. VRS efficiency also differed significantly across periods, with mean ranks of 476.25, 425.39, and 382.37, respectively. Thus, even after controlling for scale effects, pure technical efficiency was highest among firm-year observations in the pre-COVID-19 period and lowest in the most recent period.

Table 3. Results of Kruskal–Wallis Test by period.

Model	Groups	N	Mean Rank	Kruskal–Wallis's H	*p*-Value
CRS	'17–'19	285	492.68	34.050	0.000 ***
	'20–'22	285	418.13		
	'23–'25	285	373.18		
VRS	'17–'19	285	476.25	20.643	0.000 ***
	'20–'22	285	425.39		
	'23–'25	285	382.37		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The pairwise comparisons using the Mann–Whitney U test confirmed this pattern. The results of the pairwise Mann–Whitney U tests by period are presented in Table 4. For CRS efficiency, the 2017–2019 period exhibited significantly higher efficiency than the 2020–2022 period, and a significant difference was also found between 2017–2019 and 2023–2025. The difference between 2020–2022 and 2023–2025 was also statistically significant based on the reported unadjusted *p*-value. For VRS efficiency, significant differences were observed between 2017–2019 and 2020–2022, between 2017–2019 and 2023–2025, and between 2020–2022 and 2023–2025.

Table 4. Results of Mann–Whitney Test by period.

Model	Groups	N	Mean Rank	Sum of Rank	Mann–Whitney's U	Wilcoxon's W	Z	*p*-Value
CRS	'17–'19	285	311.01	88,638	33,342	74,097	−3.698	0.000 ***
	'20–'22	285	259.99	74,097				
	'17–'19	285	324.67	92,532	29,448	70,203	−5.679	0.000 ***
	'23–'25	285	246.33	70,203				
	'20–'22	285	301.14	85,826	36,154	76,909	−2.268	0.023 **
	'23–'25	285	269.86	76,909				
VRS	'17–'19	285	302.91	86,328	35,652	76,407	−2.523	0.012 **
	'20–'22	285	268.09	76,407				
	'17–'19	285	316.34	90,157	31,823	72,578	−4.471	0.000 ***
	'23–'25	285	254.66	72,578				
	'20–'22	285	300.29	85,583	36,397	77,152	−2.144	0.032 **
	'23–'25	285	270.71	77,152				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

These findings indicate that the growing social attention to AI and the expansion of market demand did not directly translate into improvements in the input–output efficiency of AI supplier firms. In particular, the fact that efficiency declined under both the CRS and VRS specifications suggests that the recent inefficiency of AI supplier firms cannot be explained solely by changes in scale structure. One possible interpretation is that, as demand for AI expanded after the COVID-19 pandemic, firms increased their investments in human resources, intangible assets, and technological infrastructure, while corresponding improvements in sales and profitability did not occur at a sufficiently rapid pace. However, the observed decline in efficiency may also reflect other market factors, such as intensified competition, pricing pressure, delays in commercialization, or dependence on a limited number of major customers.

4.3. Differences in Efficiency by Firm Age

The results of the Kruskal–Wallis test by firm age are presented in Table 5. When firms were classified into three age groups—18 years or less, 19–25 years, and 26 years or more—significant group differences were identified in CRS efficiency. The mean ranks were 415.93 for firms aged 18 years or less, 482.38 for firms aged 19–25 years, and 394.92 for firms aged 26 years or more. Thus, the intermediate age group of 19–25 years exhibited the highest CRS efficiency. Significant differences were also found for VRS efficiency, and firms aged 19–25 years again recorded the highest mean rank, at 461.45.

The results of the pairwise Mann–Whitney U tests by firm age are presented in Table 6. The post hoc comparisons showed that, under the CRS specification, firms aged 19–25 years were significantly more efficient than firms aged 18 years or less. A statistically significant difference was also observed between firms aged 19–25 years and those aged 26 years or more. In contrast, no significant difference was found between firms aged 18 years or less and those aged 26 years or more. Under the VRS specification, the difference between firms aged 18 years or less and those aged 19–25 years was statistically significant. At the 10% significance level, the difference between firms aged 18 years or less and those aged 26 years or more was also significant. However, no significant difference was observed between firms aged 19–25 years and those aged 26 years or more.

Table 5. Results of Kruskal–Wallis Test by firm age.

Model	Groups	N	Mean Rank	Kruskal–Wallis's H	*p*-Value
CRS	18 y or less	297	415.93	18.419	0.000 ***
	19–25 y	252	482.38		
	26 y or more	306	394.92		
VRS	18 y or less	297	398.24	8.974	0.011 **
	19–25 y	252	461.45		
	26 y or more	306	429.34		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Results of Mann–Whitney Test by firm age.

Model	Groups	N	Mean Rank	Sum of Rank	Mann–Whitney's U	Wilcoxon's W	Z	*p*-Value
CRS	18 y or less	297	257.21	76,392	32,139	76,392	−2.853	0.004 ***
	19–25 y	252	295.96	74,583				
	18 y or less	297	307.72	91,393	43,742	90,713	−0.794	0.427
	26 y or more	306	296.45	90,713				
	19–25 y	252	312.92	78,856	30,134	77,105	−4.444	0.000 ***
	26 y or more	306	251.98	77,105				
VRS	18 y or less	297	257.11	76,362	32,109	76,361	−2.869	0.004 ***
	19–25 y	252	296.09	74,614				
	18 y or less	297	290.13	86,168	41,915	86,168	−1.649	0.099 *
	26 y or more	306	313.52	95,939				
	19–25 y	252	291.86	73,550	35,441	82,412	−1.644	0.100
	26 y or more	306	269.32	82,412				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

These findings suggest that the relationship between firm efficiency and firm age may be nonlinear rather than simply linear, with firms in the intermediate age group of 19–25 years exhibiting relatively higher efficiency. The fact that this pattern was observed broadly under both CRS and VRS further suggests that firms aged 19–25 years may occupy a relatively advantageous position in terms of input utilization and operational efficiency.

4.4. Differences in Efficiency by Firm Size

The results of the Mann–Whitney U test by firm size are presented in Table 7. The results by firm size are noteworthy because CRS and VRS efficiency exhibited opposite patterns. For CRS efficiency, SMEs had a higher mean rank than mid-sized enterprises, at 437.36 and 368.99, respectively, and the difference between the two groups was statistically significant. In contrast, for VRS efficiency, SMEs had a mean rank of 419.42, whereas mid-sized enterprises had a mean rank of 482.12. Thus, mid-sized enterprises exhibited higher pure technical efficiency than SMEs, and this difference was also statistically significant.

These results provide important insights into the role of scale in the efficiency of AI supplier firms. When the overall input–output relationship is evaluated under the assumption of constant returns to scale, SMEs exhibit higher efficiency. However, under the VRS specification, which allows for differences in firm scale, mid-sized enterprises exhibit higher efficiency. This suggests that mid-sized enterprises may possess relatively strong operational and technical capabilities in utilizing their resources in business activi-

ties, but may not generate output performance fully proportional to their scale of inputs when firm size is also taken into account. Conversely, although SMEs exhibit lower pure technical efficiency than mid-sized enterprises, their higher CRS efficiency suggests that they may have an advantage in generating sales and profits while operating with relatively limited resources.

Table 7. Results of Mann–Whitney Test by firm size.

Model	Groups	N	Mean Rank	Sum of Rank	Mann–Whitney's U	Wilcoxon's W	Z	*p*-Value
CRS	SMEs	738	437.36	322,768	36,269	43,172	−2.782	0.005 ***
	Mid-sized	117	368.99	43,172				
VRS	SMEs	738	419.42	309,532	36,841	309,532	−2.552	0.011 **
	Mid-sized	117	482.12	56,408				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5. Differences in Efficiency by Region

The results of the Kruskal–Wallis test by region are presented in Table 8. The comparison of regional efficiency differences showed that CRS efficiency varied significantly across regions. This indicates that the distributions of CRS efficiency were not identical across Seoul, Gyeonggi, and other regions. In contrast, no statistically significant differences in VRS efficiency were found across regions. Thus, regional differences in efficiency were identified under the CRS specification but not under the VRS specification.

Table 8. Results of Kruskal–Wallis Test by region.

Model	Groups	N	Mean Rank	Kruskal–Wallis's H	*p*-Value
CRS	Seoul	558	413.78	7.827	0.020 **
	Gyeonggi	198	438.70		
	Others	99	486.76		
VRS	Seoul	558	422.26	3.227	0.199
	Gyeonggi	198	423.23		
	Others	99	469.91		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results of the pairwise Mann–Whitney U tests by region are presented in Table 9. Post hoc comparisons further showed that there was no significant difference between Seoul and Gyeonggi. In contrast, a significant difference at the 1% level was observed between Seoul and other regions, while the difference between Gyeonggi and other regions was marginally significant at the 10% level. In particular, firms located in other regions exhibited higher mean ranks, suggesting a tendency for CRS efficiency to differ between firms located in Seoul and Gyeonggi and those located in other regions. For the VRS specification, pairwise comparisons suggested marginal differences at the 10% significance level between Seoul and other regions and between Gyeonggi and other regions; however, these results should be interpreted in light of the fact that the overall regional difference was not statistically significant.

Table 9. Results of Mann–Whitney Test by region.

Model	Groups	N	Mean Rank	Sum of Rank	Mann–Whitney's U	Wilcoxon's W	Z	*p*-Value
CRS	Seoul	558	372.42	207,812	51,851	207,812	−1.284	0.199
	Gyeonggi	198	395.63	78,334				
	Seoul	558	320.85	179,037	23,076	179,037	−2.612	0.009 ***
	Others	99	374.91	37,116				
	Gyeonggi	198	142.58	28,230	8529	28,230	−1.823	0.068 *
	Others	99	161.85	16,023				
VRS	Seoul	558	377.95	210,898	54,937	210,898	−0.116	0.908
	Gyeonggi	198	380.04	75,248				
	Seoul	558	323.80	180,682	24,721	180,682	−1.667	0.096 *
	Others	99	358.29	35,471				
	Gyeonggi	198	142.69	28,253	8552	28,253	−1.790	0.073 *
	Others	99	161.62	16,000				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

These findings suggest that the geographic concentration of the AI industry in the Seoul metropolitan area does not necessarily translate into an efficiency advantage at the firm level. AI firms located in Seoul and Gyeonggi may benefit from greater access to specialized human capital, customer firms, investment institutions, and related industry networks, but they may also face relatively higher operating costs, including labor and rental expenses. In contrast, AI firms located in other regions may have achieved higher CRS efficiency by selectively allocating relatively limited resources to their core business activities, thereby generating greater output relative to their input levels.

5. Discussion and Conclusions

This study examined the operational efficiency of Korean AI supplier firms to assess whether the rapid growth and diffusion of the AI industry have translated into efficient performance generation at the firm level. To this end, the operational efficiency of AI supplier firms was estimated for the period from 2017 to 2025. An input-oriented DEA model was applied using tangible assets, intangible assets, and labor costs as input variables and sales and net income as output variables. CRS and VRS efficiency scores were then estimated separately, and differences in efficiency were examined according to period, firm age, firm size, and region.

First, the results showed that the efficiency of AI supplier firms tended to decline rather than increase over time. This suggests that, despite the growing market attention to and demand for AI following the COVID-19 pandemic, digital transformation, and the diffusion of generative AI, the overall expansion of the AI industry did not necessarily translate into improved input–output efficiency at the level of individual AI supplier firms. One possible explanation is that, in responding to market expansion, AI firms increased investments in human resources, technology, and intangible assets without proportional improvements in sales and profitability. However, this interpretation is not directly tested in the present analysis, and other factors, including intensified competition, pricing pressure, commercialization challenges, and customer concentration, may also have contributed to the observed efficiency decline.

Second, efficiency differed across firm age groups, with firms aged 19–25 years exhibiting relatively higher efficiency. This finding suggests that efficiency may not increase or decrease monotonically with firm age but may instead peak at a particular stage of organizational development. In other words, the efficiency of AI supplier firms may be associated not simply with firm age itself, but with the combination of accumulated business experience, an established customer base, organizational learning, and the flexibility required to respond to rapidly changing technological environments. In particular, firms aged 19–25 years may have accumulated sufficient market experience and organizational capabilities while retaining greater adaptability than older firms, thereby enabling relatively efficient resource utilization.

Third, the results for firm size differed between the CRS and VRS models. This indicates that firm size does not have a simple positive or negative association with the efficiency of AI supplier firms. Mid-sized enterprises may have an advantage in pure technical efficiency when scale effects are controlled for, reflecting relatively strong capabilities in managing and utilizing resources. However, when the overall input–output relationship, including scale, is considered, SMEs may exhibit relatively higher efficiency. Therefore, the growth of AI firms should not be evaluated solely in terms of increases in organizational size. Rather, attention should also be given to whether resource allocation and revenue-generation structures are appropriate for the scale at which firms operate.

Fourth, regional differences in efficiency were not clearly observed under the VRS model, whereas firms located in regions outside Seoul and Gyeonggi exhibited relatively higher efficiency under the CRS model. Firms located in the Seoul metropolitan area may benefit from greater access to human capital, business networks, customers, and investment resources, but may also face higher labor and operating costs. In contrast, firms located in other regions may achieve relatively high efficiency by selectively allocating more limited resources to their core business activities. Regional differences in efficiency should therefore be interpreted not simply as the direct effect of geographic location, but as the outcome of the combined influence of firm size, cost structure, resource input levels, and scale efficiency.

This study makes several academic contributions. First, whereas previous AI-related studies have primarily focused on the capabilities and performance of firms that adopt or utilize AI, this study examines the efficiency of firms that directly supply AI technologies and services. In doing so, it extends the literature by providing a supply-side perspective on the AI industry. Second, rather than relying solely on absolute measures of financial performance, such as sales or net income, this study evaluates AI firm performance from the perspective of resource utilization by examining the relative efficiency with which tangible assets, intangible assets, and human capital are converted into market performance and profitability. Third, by jointly examining CRS and VRS efficiency, this study demonstrates that differences associated with firm characteristics may manifest differently in overall technical efficiency and pure technical efficiency after controlling for scale effects. In particular, the contrasting results between the two models for firm size and region highlight the importance of explicitly considering scale effects when evaluating the efficiency of AI supplier firms. As a result, from a sustainability perspective, this study further demonstrates that the growth of the AI industry should be evaluated not only by the expansion of investment, employment, or market size, but also by firms' ability to convert their resources efficiently into viable economic outcomes. In this respect, operational efficiency provides a firm-level perspective for assessing whether the rapid growth of the AI industry is supported by economically sustainable resource utilization and performance generation.

The findings also have important policy implications. The performance of AI industry support policies should be assessed using a broader set of criteria. Rather than evaluating

policy outcomes solely on the basis of external growth indicators, such as the number of firms, investment volume, employment growth, or increases in sales, policymakers should also consider how efficiently invested resources are converted into actual market performance and profitability. In particular, the relatively low CRS and VRS efficiency observed in the more recent period suggests that increased investment in the AI industry does not necessarily imply the establishment of sustainable revenue structures at the firm level. Therefore, policies supporting technological development should be accompanied by measures that facilitate the commercialization of products and services, the acquisition of stable customers, the development of repeatable and sustainable revenue models, and the efficient management of input resources.

Furthermore, rather than adopting uniform support measures across firms, differentiated policy frameworks should be developed in accordance with firms' stages of growth, resource structures, firm size, and regional characteristics. More specifically, relatively younger firms may benefit from support focused on commercialization capabilities, customer acquisition, and efficient resource allocation, whereas firms in the intermediate age group may require support for market expansion while maintaining operational efficiency. For older firms, technological renewal and organizational adaptation may be more relevant. In terms of firm size, SMEs may benefit from support for efficient scaling and market expansion, while mid-sized enterprises may require greater attention to scale optimization and resource allocation. Regional support may also need to reflect differences in business environments. Firms in the Seoul metropolitan area may benefit from measures addressing relatively high labor and operating costs, whereas firms outside the capital region may require stronger access to specialized human capital, customers, investment networks, and commercialization opportunities.

This study has several limitations. First, the sample was restricted to firms registered as AI suppliers for which complete financial data were available for the entire 2017–2025 period. Because the analysis was based on firms with complete financial data throughout the study period, the sample may be subject to survivorship bias by excluding firms that entered, exited, or lacked continuous financial records. In addition, although the sampled firms were identified as AI solution suppliers in the 2026 AI Voucher supplier pool, the available data do not indicate when each firm first began supplying AI solutions. Accordingly, financial data from earlier years should be interpreted as firm-level financial performance rather than as financial outcomes exclusively attributable to AI-related business activities. Therefore, caution is required when generalizing the findings to the entire population of Korean AI firms. Future research should include newly established firms and large enterprises to examine efficiency differences across a broader range of growth stages and firm sizes. Second, because all firm-year observations from 2017 to 2025 were evaluated against a single pooled DEA frontier, this study could not distinguish shifts in the technological frontier over time from changes in the efficiency of individual firms. Future studies could employ the Malmquist Productivity Index or DEA window analysis to distinguish efficiency change from technological change. Third, because the analysis primarily relied on financial variables, including tangible assets, intangible assets, labor costs, sales, and net income, it was not possible to incorporate variables that more directly capture AI-specific characteristics, such as AI-related R&D expenditures, patents, specialized AI personnel, or the share of revenue generated from AI-related activities. More detailed AI-specific variables were not consistently available across firms and years, and their inclusion would have substantially reduced the number of complete observations available for the longitudinal analysis. Finally, the nonparametric tests employed in this study identify differences in efficiency according to period, firm age, firm size, and region, but do not establish that these characteristics directly determine efficiency. Future research

should therefore incorporate a broader set of AI-specific variables and combine DEA with panel-data analysis or two-stage DEA approaches to provide a more rigorous examination of the determinants of efficiency among AI supplier firms.

Author Contributions: Conceptualization, Y.-K.J. and S.Y.; methodology, S.Y.; software, S.Y.; validation, Y.-K.J.; formal analysis, S.Y.; investigation, Y.-K.J.; resources, Y.-K.J.; data curation, S.Y.; writing—original draft preparation, Y.-K.J.; writing—review and editing, S.Y.; visualization, Y.-K.J.; supervision, S.Y.; project administration, S.Y.; funding acquisition, Y.-K.J. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by an Electronics and Telecommunications Research Institute (ETRI) grant funded by the Korean government [26ZV1140, Promoting Commercialization of ETRI R&D Results] and the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2024S1A5C2A02046448).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data reported in this paper will be shared by the corresponding author upon reasonable request.

Acknowledgments: We gratefully acknowledge the support and assistance provided by the participating institutions and universities that contributed to this research.

Conflicts of Interest: The authors declare no conflicts of interest.

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