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A Study on the Managerial Efficiency Analysis and Evaluation Process of the Edu-Tech Industry: Focusing on the KOSDAQ Market

Hyunwoo Goh[1*]

[1] *Seokyeong University,* KOREA

***Corresponding Author:** skuie@naver.com

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ABSTRACT

The COVID-19 pandemic spurred the digital transformation of the Edu-Tech industry, promoting the development of online learning platforms, AI-based personalized education, and data-driven learning technologies. This study analyzes the managerial efficiency of Korean Edu-Tech companies listed on the KOSDAQ market, focusing on the peak period of the pandemic. Using Data Envelopment Analysis (DEA), a non-parametric analytical method, the study evaluates the relative efficiency of firms, identifies the causes of inefficiency, and demonstrates a process for setting improvement targets. The findings provide implications for enhancing the competitiveness and sustainability of Edu-Tech companies in the rapidly evolving digital education environment.

Keywords: Edu-Tech, Managerial Efficiency, COVID-19, Data Envelopment Analysis (DEA), KOSDAQ

INTRODUCTION

The COVID-19 pandemic made remote education indispensable, leading to a rapid acceleration in the growth of the Edu-Tech industry. With the widespread adoption of online learning platforms, AI tutors, and video conferencing tools, the digital transformation of education has gained significant momentum. In the future, the industry is expected to further evolve through personalized learning, metaverse-based education, and AI-driven assessment systems.

During the pandemic, Edu-Tech companies advanced their technologies in several key areas.

First, online learning platforms were enhanced. Tools such as Zoom and Google Classroom strengthened their real-time video lecture and assignment management functions. Second, AI-based personalized learning was introduced. Platforms like Duolingo and Scalastic analyzed learners' levels and patterns to provide customized content. Third, interactive content development expanded. Immersive learning environments utilizing AR and VR technologies—such as Labster's virtual laboratories—became more prevalent. Fourth, data analytics technologies advanced. Learning analytics, which analyze behavioral data to enhance learning efficiency and engagement, have developed rapidly. Fifth, collaboration and management systems were expanded. Integrated management tools such as ClassDojo and Canvas improved communication among teachers, students, and parents. Sixth, the Edu-Tech startup ecosystem grew significantly. With the government's Digital New Deal policy support, technologies such as smart learning, AI tutoring, and learning analytics were quickly commercialized.

Through the COVID-19 pandemic, the digital transformation of Korea's Edu-Tech industry was accelerated. Supported by the government's Digital New Deal initiative, these technological advancements laid the foundation for continuous growth and global market expansion.

Meanwhile, during the pandemic, the rapid response of Edu-Tech companies became a matter of survival in the market. As a result, management efficiency emerged as a crucial factor for competitiveness, prompting a series of related studies.

GOH (2020) analyzed both static and dynamic efficiency of 18 Edu-Tech firms from 2014 to 2018 using publicly disclosed management data. The study assessed overall efficiency, trends, and stability through the DEA/Window method, employing assets, liabilities, and capital as input variables, and sales, operating income, and net income as output variables. GOH (2023) applied the DEA/Window method to analyze the dynamic efficiency of 18 Edu-Tech companies from 2017 to 2022, evaluating efficiency trends and stability. Furthermore, to examine the difference in management efficiency before and during the COVID-19 pandemic, a paired-samples t-test was conducted, identifying statistically significant differences. The same input (assets, liabilities, capital) and output (sales, operating income, net income) variables were used.

However, although prior studies performed dynamic analyses of management efficiency trends over multiple years, GOH (2020) only examined the pre-pandemic period, while GOH (2023) did not sufficiently reflect the pandemic period, reducing the practical relevance of its findings.

In addition, the firms analyzed in previous studies were listed on Korea's stock markets, ensuring transparency and reliability of data. At that time, Korea's stock market was divided into two segments operated by the Korea Exchange (KRX): the Korea Composite Stock Price Index (KOSPI) market and the Korea Securities Dealers Automated Quotations (KOSDAQ) market. KOSPI comprises large, stable, and blue-chip companies, characterized by market reliability and a high proportion of institutional and foreign investors. In contrast, KOSDAQ mainly consists of venture-oriented companies focusing on technological capability and innovation, with a larger share of individual investors.

Previous studies combined firms from both markets as a single sample for efficiency evaluation. However, since the characteristics of these markets differ substantially, such an integrated approach is not appropriate for measuring relative efficiency.

Therefore, this study separates firms by market segment (KOSPI and KOSDAQ) when selecting research subjects and focuses on the period at the peak of the COVID-19 pandemic to analyze management efficiency. The analytical tool employed is Data Envelopment Analysis, a non-parametric method capable of measuring relative efficiency.

Through this analysis, the study aims to evaluate firms' relative efficiency, identify the causes of inefficiency, and set improvement targets. Ultimately, it seeks to propose analytical methods that help firms enhance their competitiveness.

A Review 0f DEA Theory

Definition of Efficiency

For a firm to achieve sustainable growth, it is essential to measure inefficiencies occurring in its operations and establish improvement strategies through objective evaluations. Concepts frequently used to assess corporate efficiency include efficiency, productivity, and effectiveness.

Efficiency is often used interchangeably with productivity, sometimes regarded as a narrow definition of productivity, while in other cases, productivity is viewed as a broader concept encompassing efficiency and performance indicators such as effectiveness and capability. Efficiency emphasizes minimal resource input, whereas productivity focuses on maximizing output, reflecting different perspectives. In contrast, effectiveness denotes to the extent to which objectives are actually achieved and is therefore considered separately. In other words, effectiveness evaluates output by measuring how well-planned objectives are met with given inputs, whereas efficiency focuses on the appropriate use of input resources to achieve the specified objectives.

Corporate efficiency represents a crucial managerial concept that indicates a firm's ability to generate maximum value and achieve goals within available resources. It plays a significant role in multiple areas, influencing not only economic performance but also competitiveness, sustainability, and stakeholder relations. To operate efficiently, firms must realize efficiency across various dimensions. For example, operational efficiency in production processes can reduce costs and increase output. Efficient decision-making processes within an organization can enhance the effectiveness of leadership and organizational culture.

The concept of efficiency was systematically formalized by Farrell (1957), who proposed that a firm's overall efficiency (OE) is determined by technical efficiency (TE), representing physical aspects, and price efficiency (PE), representing economic aspects. Technical efficiency refers to a company's ability to produce the maximum output from given inputs, while price efficiency relates to the firm's ability to determine the optimal combination of inputs from the perspective of input prices (Farrell, 1957).

When an organization operates efficiently, it can achieve objectives using minimal resources such as time, cost, and labor. Through effective management, redundant tasks and waste can be eliminated, thereby reducing costs and improving efficiency. This allows firms to deliver products and services faster and at lower costs than competitors, while resource optimization enhances organizational sustainability and resilience (Farrell, 1957). Efficiency is thus a relative measure, often expressed as a ratio of inputs to outputs, where the most efficient entity is assigned a value of '1'.

As efficiency reflects how effectively resources are utilized to generate outputs, it is a critical factor in measuring corporate performance. Accordingly, this study aims to evaluate the efficiency of Korean Edu-Tech firms, focusing on DEA, one of the representative methods for efficiency assessment.

DEA

DEA (Data Envelopment Analysis) is a statistical method used for evaluating efficiency. First proposed by Charnes et al. (1978), DEA measures the efficiency of DMUs with multiple inputs and multiple outputs by calculating the ratio of the weighted sum of outputs to the weighted sum of inputs, and then compares this with the efficiency of other DMUs performing similar activities to determine relative efficiency (Charnes et al., 1978). DEA can be classified as input-oriented and output-oriented based on the perspective of inputs and outputs.

Among the commonly used models are the CCR and BCC models. First, regarding the CCR model, Charnes et al. (1978) reinterpreted and generalized Farrell's (1957) efficiency concept, which measured a single output, and extended it to a ratio model involving multiple inputs and multiple outputs. This model, called the CCR (Charnes-Cooper-Rhodes) model, assumes constant returns to scale (CRS), meaning that returns are proportionate to scale (Avkiran, 1999).

In the input-oriented CCR model, the ratio of output to input weights for each DMU being assessed should not exceed one, and all input and output weights are required to be non-negative. In contrast, the output-oriented model applies to controllable outputs and uncontrollable inputs, assuming that the ratio of output weights to input weights is greater than or equal to '1', while minimizing the weighted sum of inputs. The efficiency derived from the CCR model is referred to as technical efficiency (TE). However, since the CCR model assumes CRS (constant returns to scale), it cannot distinguish whether inefficiency arises from internal operational technical inefficiency or from scale inefficiency.

Next, the BCC model, maded by Banker et al. (1984), was designed to overcome the CCR model's limitation by assuming that all DMUs operate at an optimal scale. This allows for the distinction between scale efficiency (SE) and pure technical efficiency (PTE). The BCC model assumes variable returns to scale (VRS), meaning that outputs may increase more or less than inputs proportionally. Under this assumption, input-minimization and output-maximization models may yield different results, allowing a more precise evaluation of managerial efficiency. Thus, by accounting for variable returns to scale, the BCC model overcomes the CCR model's limitation and enables the determination of pure technical efficiency (PTE), which excludes scale effects.

The input-oriented CCR model is expressed as a formula as shown in equation (1). M and N represent the types of inputs and outputs, respectively, and J represents the number of observations.

$$\theta^{k^*} = \min_{\theta,\lambda} \theta^k \qquad (1)$$

Subject to

$$\theta^k x_m^k \geq \sum_{j=1}^{J} x_m^j \lambda^j \quad (m = 1, 2, \cdots, M);$$

$$y_n^k \leq \sum_{j=1}^{J} y_n^j \lambda^j (n = 1, 2, \cdots, N);$$

$$\lambda^j \geq 0 \; (j = 1, 2, \cdots, J)$$

The input-oriented BCC model is mathematically represented in equation (2).

$$\theta^{k^*} = \min_{\theta,\lambda} \theta^k \qquad (2)$$

Subject to

$$\theta^k x_m^k \geq \sum_{j=1}^{J} x_m^j \lambda^j (m = 1, 2, \cdots, M);$$

$$y_m^k \leq \sum_{j=1}^{J} y_n^j \lambda^j (n = 1, 2, \cdots, N);$$

$$\sum_{j=1}^{J} \lambda^j = 1;$$

$$\lambda^j \geq 0 \; (j = 1, 2, \cdots, J)$$

SE and RTS

Scale Efficiency (SE) is an indicator that evaluates whether a Decision-Making Unit (DMU) operates at the most efficient production scale. SE can be calculated using the CCR and BCC models. The CCR model assumes CRS (Chanrnes et al. 1978) and measures Technical Efficiency (TE), while the BCC model assumes VRS (Banker et al. 1984) and measures Pure Technical Efficiency (PTE). Accordingly, SE can be derived as shown in Equation (3).

$$SE = \frac{\theta^*(CCR)}{\theta^*(BCC)} = \frac{Technical\ Efficiency(TE)}{Pure\ Technical\ Efficiency(PTE)} \qquad (3)$$

$$= \frac{Pure\ Technical\ Efficiency(PTE) \times\ Scale\ Efficiency(SE)}{Pure\ Technical\ Efficiency(PTE)}$$

SE has a value between '0' and '1', and when SE is '1', it means that the DMU is in the CRS state, which is the most optimal scale level. On the other hand, when SE is less than 1, it means that the DMU is in the increasing return to scale (IRS) or decreasing return to scale (DRS) state. In order to determine whether a DMU with SE less than 1 is in the IRS or DRS state, the input-direction BCC model indicates a DRS state if the efficiency value of the input-direction CCR model and the efficiency value of the modified constraint $0 < \sum_{j=1}^{n} \lambda_j \leq 1$ are equal, and an IRS state if the efficiency value of $\sum_{j=1}^{n} \lambda_j \geq 1$ is equal.

Returns to Scale (RTS) refers to the relationship between the increase in input factors and the resulting change in output, and it serves as an important indicator for assessing the efficiency of production scale.

In the case of IRS, the output increases by a greater proportion than the input, indicating that the current production scale is relatively small.

Therefore, expanding the scale of production can potentially improve efficiency.

On the other hand, CRS represents a state in which inputs and outputs increase in the same proportion. This implies that the DMU operates at an optimal scale, and there is little room for efficiency improvement through scale adjustment.

Finally, DRS describes a condition in which output increases by a smaller proportion than input. This suggests that the current production scale is excessively large, and reducing the scale of operation may lead to greater efficiency.

Empirical Analysis of DEA

This study focuses on 15 Edu-Tech companies listed on the KOSDAQ in 2022, which was the peak period of the COVID-19 pandemic. Using actual data, the study analyzes the efficiency of these companies.

Selection of Input and Output Variables

The selection of input and output variables was based on previous studies, and financial statement data were used to address managerial efficiency.

For the candidate input variables, assets, liabilities, and equity were considered, while sales, operating profit, and net income were selected as candidate output variables. The data were obtained from the financial statements of each company to reflect their managerial conditions.

A correlation analysis was conducted among the candidate variables to identify final variables that exhibited a strong correlation between inputs and outputs while maintaining relatively low multicollinearity among the input variables.

As a result, liabilities and equity were selected as the input variables, and sales was selected as the output variable. Table 1 summarizes the descriptive statistics of these variables.

Table 1: Descriptive Statistics of Input/Output Variables

(unit: hundred million won)			
Factor Statistics	**Input factor**		**output factor**
	Liabilities	**Capital**	**Sales**
Max	4,710	4,337	9,333
Min	21	44	95

Average	1,244	1,606	2,646
SD	1,446	1,479	2,958

CCR-I Model Efficiency Analysis

The input-oriented CCR model was employed to analyze technical efficiency.

The resulting efficiency scores range between 0 and 1. A score '1' indicates that the DMU has reached the efficient frontier, while a score below 1 indicates inefficiency. Among the 15 DMUs, three (D01, D13, and D15) were relatively efficient, whereas the remaining 12 DMUs were classified as inefficient.

The DMUs were ranked in descending order based on their efficiency scores. The average technical efficiency of the 15 DMUs was 0.79, with a standard deviation (SD) of 0.16, and the minimum efficiency was 0.504 for D08 (<Table 2>).

Table 2: Results of the CCR-I model

DMU	Score	Rank	Reference (Lambda)				Reference count
D01	1	1	D01	(1)			11
D02	0.842	7	D01	(0.538)	D13	(1.568)	
D03	0.864	5	D01	(1.883)	D13	(0.836)	
D04	0.851	6	D01	(1.474)	D15	(12.911)	
D05	0.728	10	D01	(0.157)	D13	(0.703)	
D06	0.561	14	D01	(0.154)	D15	(0.236)	
D07	0.887	4	D01	(0.173)	D13	(1.557)	
D08	0.504	15	D01	(0.183)	D13	(4.743)	
D09	0.675	12	D15	(7.231)			
D10	0.666	13	D01	(0.019)	D13	(0.213)	
D11	0.677	11	D01	(1.447)	D15	(10.126)	
D12	0.833	8	D01	(0.144)	D15	(1.113)	
D13	1	1	D13	(1)			7
D14	0.738	9	D01	(0.675)	D13	(0.989)	
D15	1	1	D15	(1)			5

BCC-I Model Efficiency Analysis

Among the 15 DMUs, seven (D01, D03, D04, D09, D10, D13, and D15) were found to be efficient, while the remaining eight DMUs were classified as inefficient.

The DMUs were ranked in descending order based on their efficiency scores. The average pure technical efficiency of the 15 DMUs was 0.88, with a standard deviation of 0.15, and the minimum efficiency was 0.59 for DMU D06 (<Table 3>).

Table 3: Results of the BCC-I model

DMU	Score	Rank	Reference (Lambda)						Reference count
D01	1	1	D01	(1)					8
D02	0.868	9	D01	(0.576)	D13	(0.424)			
D03	1	1	D03	(1)					1
D04	1	1	D04	(1)					2

D05	0.736	13	D01	(0.147)	D13	(0.765)	D15	(0.087)	
D06	0.591	15	D01	(0.110)	D13	(0.246)	D15	(0.644)	
D07	0.938	8	D01	(0.198)	D13	(0.802)			
D08	0.622	14	D01	(0.318)	D13	(0.682)			
D09	1	1	D09	(1)					0
D10	1	1	D10	(1)					0
D11	0.789	11	D01	(0.134)	D03	(0.080)	D04	(0.786)	
D12	0.863	10	D01	(0.116)	D04	(0.019)	D15	(0.865)	
D13	1	1	D13	(1)					6
D14	0.749	12	D01	(0.698)	D13	(0.302)			
D15	1	1	D15	(1)					3

Reference Set Analysis

One of the primary purposes of efficiency evaluation is to improve the performance of inefficiently evaluated DMUs compared to those that are assessed as efficient (Odeck and Alkadi, 2001).

The **Reference Set** refers to the group of efficient DMUs that an inefficient DMU should benchmark in order to become efficient. In other words, when an inefficient DMU is projected onto the efficient frontier, the efficient DMUs that form the projection point constitute its Reference Set.

The **Reference Count** indicates how many times each efficient DMU appears in the reference sets of other inefficient DMUs. A DMU with a high Reference Count is frequently used as a benchmark for many inefficient DMUs and can therefore be regarded as a key DMU with an exemplary efficiency pattern. Conversely, a DMU with a low Reference Count, while efficient, is considered a less useful benchmark for other DMUs.

Inefficiently evaluated DMUs tend to refer to efficient DMUs that have similar input combinations; hence, they can be utilized as alternatives for improving future efficiency.

<Table 2> and <Table 3> summarize the 'reference counts' and 'reference sets' of efficiently evaluated DMUs under the CCR-I and BCC-I models, respectively.

In the CCR-I model, three efficient firms were identified, with DMU D01 being referenced 11 times, DMU D13 seven times, and DMU D15 five times. In the BCC-I model, seven efficient DMUs were observed, with DMU D01 showing the highest reference count of eight. Therefore, DMU D01, which has a high reference count in both the CCR and BCC models, deserves particular attention

Setting Improvement Target Values

The purpose of efficiency evaluation is to enable inefficient DMUs to benchmark against efficient DMUs and improve their efficiency. In other words, inefficient DMUs refer to efficient DMUs that form similar input combinations.

Based on the reference sets and reference counts from the CCR-I and BCC-I models shown in Table 2 and Table 3, DMUs for benchmarking can be selected. This allows the setting of improvement target values (Table 4 and Table 5).

In the tables, 'Data' represents the current values, 'Projection' indicates the improvement target values, and 'Diff (%)' shows the percentage difference between 'Data' and 'Projection'. For example, DMU D08 in Table 4 is the most inefficient in terms of technical efficiency. To become efficient, it must reduce the input variable Liabilities from KRW 633 billion to KRW 319 billion and the other input variable Capital from KRW 3,405 billion to KRW 1,716 billion, corresponding to a reduction of 49.6%.

Similarly, in Table 5, DMU D06, which has the lowest pure technical efficiency, must reduce the input variable Liabilities from KRW 398 billion to KRW 230 billion, a 40.9% decrease, and the other input variable Capital from KRW 492 billion to KRW 291 billion, a 40.9% reduction, in order to become efficient.

Table 4: Target value for improvement of CCR-I

(unit: hundred million won)						
DMU	Liabilities			Capital		
	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
D01	1,194	1,194	0	1,724	1,724	0
D02	802	675	-15.8	1,652	1,390	-15.8
D03	2,623	2,266	-13.6	4,044	3,493	-13.6
D04	4,259	3,626	-14.9	3,649	3,107	-14.9
D05	278	202	-27.2	657	478	-27.2
D06	389	218	-43.9	492	276	-43.9
D07	270	239	-11.3	854	758	-11.3
D08	633	319	-49.6	3,405	1,716	-49.6
D09	1,772	1,045	-41.0	469	317	-32.5
D10	42	28	-33.4	145	97	-33.4
D11	4,710	3,191	-32.3	4,337	2,938	-32.3
D12	400	333	-16.7	357	297	-16.7
D13	21	21	0	295	295	0
D14	1,120	827	-26.2	1,972	1,456	-26.2
D15	145	145	0	44	44	0

Table 5: Target value for improvement of BCC-I

(unit: hundred million won)						
	Liabilities			Capital		
DMU	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
D01	1,194	1,194	0.0	1,724	1,724	0.0
D02	802	696	-13.2	1,652	1,118	-32.3
D03	2,623	2,623	0.0	4,044	4,044	0.0
D04	4,259	4,259	0.0	3,649	3,649	0.0
D05	278	205	-26.4	657	484	-26.4
D06	389	230	-40.9	492	291	-40.9
D07	270	253	-6.2	854	578	-32.4
D08	633	394	-37.8	3,405	749	-78.0
D09	1,772	1,772	0.0	469	469	0.0
D10	42	42	0.0	145	145	0.0
D11	4,710	3,716	-21.1	4,337	3,422	-21.1
D12	400	345	-13.7	357	308	-13.7
D13	21	21	0.0	295	295	0.0
D14	1,120	839	-25.1	1,972	1,292	-34.5

D15	145	145	0.0	44	44	0.0

SE and RTS Analysis

Table 6 summarizes Scale Efficiency (SE), the cause of inefficiency, and Returns to Scale (RTS).

Scale efficiency reflects the efficiency related to the optimization of production scale in the production relationship between input and output, i.e., the ability of a DMU to operate at an optimal scale. SE can be calculated by dividing the technical efficiency from the CCR model by the pure technical efficiency from the BCC model (<Table 6>).

When SE equals 1, the DMU is considered to be operating at full scale efficiency. If PTE > SE, the cause of inefficiency is attributed to scale inefficiency (SE), whereas if PTE < SE, the inefficiency is interpreted as being due to pure technical inefficiency (PTE).

Among the DMUs, three (D05, D06, and D10) exhibit IRS, indicating that they need to expand their scale of operation to improve efficiency. Seven DMUs (D01, D02, D07, D08, D13, D14, and D15) show CRS, meaning they are operating at an optimal scale and should maintain their current level. Five DMUs (D03, D04, D09, D11, and D12) exhibit DRS, suggesting that they should reduce their scale of operation to enhance efficiency.

Table 6: Summary of SE, cause of inefficiency and RTS

DMU	**Efficiency score**		**SE**	**Cause of inefficiency**		**RTS**
	CCR(TE)	**BCC(PTE)**		**PTE**	**SE**	
D01	1	1	1			CRS
D02	0.842	0.868	0.970	o		CRS
D03	0.864	1	0.864		o	DRD
D04	0.851	1	0.851		o	DRD
D05	0.728	0.736	0.989	o		IRS
D06	0.561	0.591	0.950	o		IRS
D07	0.887	0.938	0.945	o		CRS
D08	0.504	0.622	0.810	o		CRS
D09	0.675	1	0.675		o	DRS
D10	0.666	1	0.666		o	IRS
D11	0.677	0.789	0.859	o		DRD
D12	0.833	0.863	0.965	o		DRD
D13	1	1	1			CRS
D14	0.738	0.749	0.985	o		CRS
D15	1	1	1			CRS

CONCLUSION

This study was conducted to respond to the paradigm shift in the Edu-Tech industry following the COVID-19 pandemic and to explore strategies for enhancing firms' managerial efficiency. In particular, the analysis focused on the year 2022, the peak period of the pandemic, and examined 15 Edu-Tech companies. The input variables were selected as liability and capital, while sales was chosen as the output variable. Data for these variables were obtained from the financial statements of Edu-Tech firms listed on the KOSDAQ, ensuring objectivity and transparency.

For the efficiency evaluation, the Data Envelopment Analysis (DEA) methodology was employed. Specifically, the input-oriented CCR model and input-oriented BCC model were adopted to analyze technical efficiency and pure technical efficiency, respectively.

The evaluation and analysis were conducted in three steps: First, the relative efficiencies of the 15 firms were measured, and ranking analysis was performed to distinguish between efficient and inefficient firms. Second, the reference sets and reference counts were analyzed to enable inefficient firms to identify efficient peers for benchmarking, and a method was presented to calculate target improvement values for input variables. Third, through scale efficiency (SE) analysis, the causes of inefficiency among underperforming firms were identified, and the returns to scale (RTS) analysis was used to diagnose each firm's status for enhancing efficiency.

By stratifying the target firms in comparison with previous studies, the number of output variables was reduced, thereby strengthening the dependency relationship with the input variables. This study is expected to contribute to improving the competitiveness of the Edu-Tech industry by empirically demonstrating an efficiency analysis process that can be utilized in practice. Furthermore, it highlights the need for continuous and periodic research to compare and analyze trends in corporate efficiency over time.

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