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RESEARCH ARTICLE

Analysis of Relative Efficiency of the Fashion Industry using Data Envelopment Analysis

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ABSTRACT

Fashion requires management efficiency to respond quickly to the diverse and rapidly changing needs of consumers. In this study, management data is collected from fashion companies, relative efficiency is analyzed and ranked, and management efficiency is compared and evaluated from a relative perspective. To analyze relative efficiency, data envelopment analysis (DEA) is used, and it is divided into technical efficiency and pure technical efficiency and detailed. The efficiency of inefficient fashion companies is analyzed according to the ranking order, and the process for selecting efficient companies for benchmarking by inefficient companies and the improvement target value of input factors are derived. In addition, the cause of inefficiency is determined through Scale Efficiency (SE) analysis, and the Return to Scale (RTS) of fashion companies is presented.

INTRODUCTION

The Korean fashion industry is a representative job-creating industry with 830,000 employees including related industries such as manufacturing, wholesale and retail, and service industries, and it is an industry that contributes greatly to the national life and economy. It is also an industry with large forward and backward ripple effects as it is used as a core material for other industries such as automobiles, aviation, and shipbuilding. As a result of the forward and backward ripple effects, the production inducement coefficient (2.10) exceeds the manufacturing average (1.90), so if the industry collapses, there will be serious unemployment problems, and there will also be difficulties in recycling the existing excellent human resources when the situation normalizes in the future (Jung, 2020).

In 2020, the COVID-19 pandemic brought about tremendous changes to various industries worldwide, and the fashion industry was also greatly affected. The fashion industry, which was one of the industries most affected by the pandemic, is an industry that values experiences and has the characteristics of face-to-face consumption, so the decline in sales was relatively large. Fashion products are seasonal and issue products and are sensitive to trends, so products whose orders are canceled cannot be sold normally and often remain as dead inventory (Jung, 2020).

The spread of the pandemic has accelerated the digital transformation as the importance of technology has been emphasized in all industries, and hybrid forms that combine online and offline, as well as eco-friendliness and sustainability, have become important topics, and the same applies to the textile/fashion industry. In terms of consumption, the pandemic has also affected consumers' lifestyles, creating new trends and changing their consumption patterns.

The social change factors of the pandemic phenomenon include untact, home economy, anxiety care, and egoism, and practicality and symbolism were extracted as factors in fashion purchasing behavior. The main purchasing channels for fashion products are internet and mobile shopping, and the main purchasing information acquisition channels are past purchasing experience and internet searches. Price sensitivity and brand sensitivity were extracted as factors in fashion consumption behavior, and the main fashion product purchase items were found to be going out clothes and loungewear. In other words, consumer behavior after the pandemic has the characteristics of purchasing fashion products that are essential to them and consuming brand products with proven quality at a reasonable price.

As a measure to respond to changes in the fashion industry and consumption due to the pandemic, the government should provide priority liquidity supply and employment maintenance to the fashion industry, which is experiencing financial difficulties due to the COVID-19 pandemic, and the industry should proactively respond to the post-pandemic situation by promoting digital transformation.

After the pandemic ends, the endemic will arrive, and changes in industry and society will begin again, and the fashion industry must prepare for new responses. In particular, there has been no continuous research on corporate management efficiency. In order to keep up with the advent of the endemic, it is necessary to review management efficiency and respond to changes at this point.

In this way, in the midst of rapid changes in the paradigm of the fashion industry, the analysis of corporate efficiency should be prioritized for competitiveness enhancement and sustainable growth. The efficiency and productivity of the fashion industry should be increased by digital new technologies that combine traditional fashion basic industries with IoT technology. Therefore, the efficiency of the management activities of the fashion industry should be analyzed first, and the causes of inefficiency in the fashion industry should be identified and reflected in decision-making and strategy establishment to respond to changes.

This study analyzes the management efficiency of the fashion industry after the pandemic, identifies the causes of inefficiency, and proposes a process for calculating improvement targets for inefficient companies to develop into efficient companies using the DEA methodology. The research results are intended to increase the efficiency of the fashion industry and enhance corporate competitiveness.

Review of previous research

The previous efficiency studies in the fashion industry using DEA are as follows.

Lee & Hong (2021) analyzed the efficiency of fashion retail stores by focusing on the case of fashion company 'A'. The research sample is 104 stores of fashion company A for three years from 2017 to 2019. The input variables are the number of employees, rent, and number of brands, and the output variables are sales and number of customers.

Ju et al. (2008) analyzed the efficiency of textile and fashion companies according to spatial proximity using the DEA model. The purpose of the study was to provide policy implications for fostering the textile and fashion industry by presenting efficiency values by characteristics such as proximity to consumer markets, proximity to suppliers, proximity to living bases, and proximity to clusters, which are analysis criteria according to spatial proximity.

Shin (2020) analyzed the efficiency of 22 fashion companies listed on the Korea Exchange in Korea from 2016 to 2018. They attempted to measure and decompose cost efficiency for each listed company using the directional distance function as a method of DEA. At this time, cost efficiency can be decomposed into technical efficiency and allocation efficiency. The output variable of fashion companies was value added, and the inputs were capital, labor, capital stock, number of workers, capital stock price, and labor price.

Ryu et al. (2023) aimed to identify the impact of fashion companies' operational efficiency and marketing activities on corporate social responsibility (CSR) activities. The study subjects were 223 fashion companies listed from 2011 to 2019, and the main explanatory variables were relative operational efficiency measured by DEA analysis and cost variables for marketing activities for internal and external customers, and the dependent variable was CSR scores.

Previous studies on the efficiency of the fashion industry using DEA were conducted on a portion of a specific company or a specific region, and there was no research on the fashion industry as a whole. In addition, there is a lack of research that reflects social changes after the end of the pandemic compared to research before the pandemic. Therefore, this study conducts research on the entire fashion industry based on the latest data after the pandemic.

THEORETICAL CONSIDERATIONS

Analysis model concept

Efficiency

DEA is one of the efficiency measurement techniques and is used to measure relative efficiency. DEA is used to compare the relative efficiency between DMUs (decision making units), and calculates the efficiency of DMUs based on inputs and outputs. Unlike other efficiency measurement techniques, DEA, a nonparametric efficiency measurement method, does not assume a specific functional form in advance and estimate parameters, but derives an empirical efficiency frontier using data between empirical inputs and outputs of the evaluation target based on linear programming, and then measures inefficiency by how far the evaluation targets are from the efficient frontier. That is, DEA creates an efficient frontier based on the data of DMUs and defines DMUs on that frontier as efficient DMUs, and DMUs that are not on that frontier as inefficient DMUs.

DEA can be divided into CCR and BCC models depending on whether the returns to scale change. The CCR model assumes constant returns to scale (CRS), which states that the amount of output increases when input per unit increases, and the BCC model assumes variable returns to scale (VRS), which assumes variable returns to scale (Charnes et al., 1978). The difference between the CCR and BCC models is that the CCR model simultaneously evaluates scale and technical inefficiency, while the BCC model evaluates the two separately (Charnes et al., 1978).

DEA can also be divided into input-oriented models and output-oriented models. The input-oriented model aims to fix output and minimize input, and the output-oriented model aims to fix input and maximize output (Charnes et al., 1978). In empirical analysis, one must choose between an input-oriented model and an output-oriented model, which can be determined based on the characteristics of the DMU. If output adjustment of the DMU is impossible and input can be reduced, the input-oriented model should be used, and if output adjustment of the DMU is possible, the output-oriented model should be used. In this study, the input-oriented model is used.

Input-oriented CCR (CCR-I) model

The CCR model is a model proposed by Charnes et al (1978), and assumes CRS. CRS means that when an observation exists, all points that are expanded or reduced by the same ratio can be produced. The CCR model is a linear fractional programming method that seeks to maximize the ratio of the weighted sum of outputs to the weighted sum of inputs of a DMU under the simple constraint that the ratio of the weighted sum of outputs to the weighted sum of inputs of the DMUs must not exceed 1, and the weights of each input and output factor must be greater than 0 (Park, 2017).

The input-oriented CCR model is a model that derives the ratio at which inputs can be reduced as much as possible while fixing output under the CRS assumption. In other words, when inputs are reduced the most, the ratio of the original input to the reduced input is considered as the efficiency value.

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

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

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

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

Input-oriented BCC (BCC-I) model

The CCR model has a disadvantage in that it cannot distinguish between scale efficiency and pure technical efficiency because the model is derived under the assumption of CRS (Park, 2008). The BCC model is a model proposed by Banker et al. (1984) that relaxes the CRS condition and assumes variable returns to scale (VRS). VRS refers to the case where there is decreasing returns to scale (DRS) in which output decreases more when inputs increase, or increasing returns to scale (IRS) in which output increases more when inputs increase. In the case of DRS, diseconomies of scale exist, and in the case of IRS, economies of scale exist.

The input-oriented BCC model adds a constraint that represents the convexity assumption in the input-oriented CCR model. Convexity means that if any two input-output combinations are possible, then a linear combination of the two observations can also be produced

That is, the BCC model has an additional equation constraint $\sum_{j=1}^{J} \lambda_j = 1$ that represents the convexity assumption in the CCR model, and because of this condition, it does not allow infinite reduction or expansion of observations or points that combine observations with linear internal division. Instead, only points that satisfy internal division points and free disposal among observations are recognized as possible for production. The closer the efficiency value of DMU is to 1, the higher the efficiency is, and the closer it is to 0, the lower the efficiency is. The input-oriented BCC model can be expressed as a formula as shown in equation (2).

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

Subject to

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

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

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

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

Scale efficiency (SE) and return to scale (RTS)

The difference in the efficiency scores of the CCR model and the BCC model due to the difference in the returns to scale assumptions can be expressed using the SE concept. That is, efficiency of scale refers to the difference between the production change representing the CRS and the production change under the VRS, and a DMU that shows the difference between the efficiency scores of the CCR model and the BCC model means that it has inefficiency of scale. The efficiency calculated by the BCC model assuming VRS is generally greater than or equal to the efficiency of the CCR model assuming the CRS. Some call the CCR efficiency technical efficiency (TE) and the BCC efficiency pure technical efficiency (PTE). The efficiency of scale can be expressed as a formula as shown in Equation (3).

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

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

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.

DEA ANALYSIS RESULTS

Selection of analysis subjects and input and output

The fashion companies that are the subjects of the efficiency study are DMUs, and 24 companies are the subjects of analysis. In order to select input/output factors, we referred to previous studies, and in particular, because we deal with management efficiency, we selected factors in financial statements as candidates.

Assets, liabilities, and capital were selected as input factors, and sales, operating profit, and net profit were selected as output factors, and data was collected from the financial statements for 2023, the year after COVID-19 ended. A correlation analysis of the candidate factors was performed, and factors with high correlations between input factors and output factors and relatively low correlations between input factors were selected as final factors. Finally, liabilities and capital were determined as input factors, and sales and operating profit were determined as output factors. Their statistics are shown in <Table 1>.

Table 1: Descriptive statistics of input/output factors

(unit: hundred million won)

Factor / Statistics	Input factor		output factor	
	Liabilities	Capital	Sales	Operational Profit

Max	17,092	35,880	36,044	6,371
Min	168	396	564	-42
Average	3,517	5,247	7,588	631
SD	3,884	7,603	8,311	1,293

Efficiency analysis

Input-oriented technical efficiency can be analyzed using the CCR-I model, and input-oriented pure technical efficiency can be analyzed using the BCC-I model.

CCR-I model analysis results

The efficiency obtained is between 0 and 1. If the value is 1, the DMU has reached the efficient frontier, and if it is less than 1, the DMU is evaluated as inefficient. 7 DMUs (D08, D12, D13, D14, D15, D17, D18) are efficient, and the remaining 17 DMUs are inefficient. The rankings were evaluated in descending order according to efficiency, and the mean technical efficiency of the 24 DMUs is 0.74, the standard deviation is 0.246, and the minimum is 0.183 of D02 (<Table 2>).

Table 2: Results of the CCR-I model

DMU	Score	Rank	Reference (Lambda)						Reference count
D01	0.847	10	D12	(0.114)	D15	(0.241)			
D02	0.183	24	D12	(0.345)	D17	(0.464)			
D03	0.697	15	D12	(0.150)	D17	(0.468)			
D04	0.768	14	D12	(0.073)	D15	(0.072)			
D05	0.435	21	D14	(0.361)	D17	(0.186)			
D06	0.432	22	D17	(0.479)					
D07	0.492	19	D12	(0.158)	D15	(0.092)			
D08	1	1	D08	(1)					3
D09	0.840	12	D08	(0.003)	D14	(4.107)	D17	(1.572)	
D10	0.651	16	D14	(0.730)	D17	(5.778)			
D11	0.935	8	D14	(0.687)					
D12	1	1	D12	(1)					5

D13	1	1	D13	(1)					1
D14	1	1	D14	(1)					8
D15	1	1	D15	(1)					3
D16	0.589	17	D14	(0.221)	D17	(0.150)			
D17	1	1	D17	(1)					9
D18	1	1	D18	(1)					3
D19	0.557	18	D14	(0.191)					
D20	0.455	20	D13	(0.022)	D14	(0.632)			
D21	0.770	13	D08	(0.131)	D18	(0.412)			
D22	0.844	11	D18	(0.583)					
D23	0.926	9	D08	(0.054)	D17	(0.661)	D18	(0.137)	
D24	0.421	23	D14	(0.685)	D17	(8.618)			

BCC-I model analysis results

11 DMUs (D04, D08, D09, D11, D12, D13, D14, D15, D17, D18, D19) are efficient, and the remaining 13 DMUs are inefficient. The rankings were evaluated in descending order of efficiency, and the average pure technical efficiency of the 24 DMUs was 0.84, the standard deviation was 0.22, and the minimum was 0.184 for DMU D02 (<Table 3>).

Table 3: Results of the BCC-I model

DMU	Score	Rank	Reference (Lambda)						reference count
D01	0.920	13	D04	(0.670)	D15	(0.231)	D17	(0.099)	
D02	0.184	24	D12	(0.193)	D15	(0.083)	D17	(0.725)	
D03	0.735	19	D04	(0.232)	D15	(0.051)	D17	(0.718)	
D04	1	1	D04	(1)					5
D05	0.520	22	D14	(0.202)	D17	(0.273)	D19	(0.525)	
D06	0.901	14	D04	(0.001)	D17	(0.999)			
D07	0.560	21	D04	(0.720)	D15	(0.097)	D17	(0.184)	

D08	1	1	D08	(1)					4
D09	1	1	D09	(1)					2
D10	0.847	16	D08	(0.518)	D09	(0.225)	D17	(0.256)	
D11	1	1	D11	(1)					0
D12	1	1	D12	(1)					1
D13	1	1	D13	(1)					2
D14	1	1	D14	(1)					2
D15	1	1	D15	(1)					4
D16	0.836	17	D17	(0.282)	D19	(0.718)			
D17	1	1	D17	(1)					10
D18	1	1	D18	(1)					3
D19	1	1	D19	(1)					3
D20	0.490	23	D13	(0.026)	D14	(0.431)	D19	(0.544)	
D21	0.802	18	D08	(0.094)	D17	(0.471)	D18	(0.434)	
D22	0.900	15	D04	(0.417)	D18	(0.583)			
D23	0.952	12	D08	(0.044)	D17	(0.814)	D18	(0.142)	
D24	0.599	20	D08	(0.776)	D09	(0.165)	D13	(0.059)	

Reference analysis

One of the main reasons for efficiency evaluation is to improve the performance of inefficiently evaluated DMUs compared to efficiently evaluated DMUs (Odeck and Alkadi, 2001). Since inefficiently evaluated DMUs refer to DMUs that form similar input combinations among efficient DMUs, they can be used as alternatives for future efficiency improvement. <Table 2> and <Table 3> summarize the reference counts and reference sets of DMUs evaluated efficiently in the CCR-I model and the BCC-I model. In the CCR-I model, 7 efficient firms were observed, and the reference counts were 9 for D17 and 8 for D14 DMUs. In the BCC-I model, 11 efficient DMUs were observed, and the DMU with the highest reference count was D17, which was referenced 10 times. It is noteworthy that DMU D17, which commonly has a high reference count in both the CCR model and the BCC model, has a high reference count.

In the case of DMUs with a high reference count, inefficient DMUs can be interpreted as good reference DMUs for benchmarking. On the other hand, in the case of DMUs that are evaluated as efficient but have a low reference count, it can be concluded that they are not good reference DMUs for benchmarking because they are likely to form heterogeneous input combinations. In the case where there is no DMU among efficient DMUs with a low reference count that inefficient DMUs can refer to, it is considered desirable to mainly refer to the DMU with the most similar environment or the DMU with the most similar operating scale.

Improvement target value analysis

The purpose of efficiency evaluation is to improve the efficiency of inefficient DMUs. In other words, inefficiently evaluated DMUs refer to efficient DMUs that form similar input combinations. In <Table 2> and <Table 3>, the reference sets and reference counts of the CCR-I model and the BCC-I model can be used to select DMUs to benchmark. Through this, the improvement target value can be found (<Table 4>, <Table 5>). In the table, 'Data' refers to the current value, 'Projection' refers to the improvement target value, and Diff.(%) refers to the percentage difference between 'Data' and 'Projection'. For example, DMU D02 in <Table 4> has the most inefficient technical efficiency, and to become an efficient DMU, the input factor 'Liabilities' should be reduced by 81.7% from the current KRW 7,452 billion to KRW 1,362 billion, and another input factor, 'Capital', should be reduced by 81.7% from KRW 5,640 billion to KRW 1,031 billion.

Similarly, in order for DMU D02, which has the lowest pure technical efficiency in <Table 5>, to become an efficient DMU, the input factor 'Liabilities' must be reduced by 81.6% from the current KRW 7,452 billion to KRW 1,374 billion, and another input factor, 'Capital', must be reduced by 81.6% from KRW 5,640 billion to KRW 1,040 billion.

Table 4: Target value for improvement of CCR-I

(unit: hundred million won)

DMU	Liabilities			Capital		
	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
D01	1,807	1,531	-15.3	878	744	-15.3
D02	7,452	1,362	-81.7	5,640	1,031	-81.7
D03	1,028	716	-30.3	883	615	-30.3
D04	760	583	-23.2	396	304	-23.2
D05	607	264	-56.5	2,428	1,056	-56.5
D06	522	226	-56.8	699	302	-56.8
D07	1,955	962	-50.8	1,073	528	-50.8
D08	6,052	6,052	0	7,546	7,546	0
D09	3,299	2,771	-16.0	13,943	11,710	-16.0
D10	4,724	3,073	-34.9	8,517	5,541	-34.9
D11	360	337	-6.5	3,657	1,788	-51.1

D12	3,312	3,312	0	2,138	2,138	0
D13	17,092	17,092	0	35,880	35,880	0
D14	490	490	0	2,604	2,604	0
D15	4,788	4,788	0	2,077	2,077	0
D16	303	179	-41.1	1,136	669	-41.1
D17	470	470	0	630	630	0
D18	6,458	6,458	0	4,239	4,239	0
D19	168	94	-44.3	1,075	497	-53.7
D20	1,507	686	-54.5	5,349	2,436	-54.5
D21	4,486	3,455	-23.0	3,553	2,736	-23.0
D22	4,701	3,765	-19.9	2,928	2,471	-15.6
D23	1,643	1,522	-7.4	1,517	1,405	-7.4
D24	10,421	4,386	-57.9	17,136	7,212	-57.9

Table 5: Target value for improvement of BCC-I

(unit: hundred million won)

DMU	Liabilities			Capital		
	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
D01	1,807	1,662	-8.0	878	807	-8.0
D02	7,452	1,374	-81.6	5,640	1,040	-81.6
D03	1,028	756	-26.5	883	649	-26.5
D04	760	760	0	396	396	0
D05	607	316	-48.0	2,428	1,262	-48.0
D06	522	470	-9.9	699	630	-9.9
D07	1,955	1,096	-44.0	1,073	601	-44.0

D08	6,052	6,052	0	7,546	7,546	0
D09	3,299	3,299	0	13,943	13,943	0
D10	4,724	4,001	-15.3	8,517	7,214	-15.3
D11	360	360	0	3,657	3,657	0
D12	3,312	3,312	0	2,138	2,138	0
D13	17,092	17,092	0	35,880	35,880	0
D14	490	490	0	2,604	2,604	0
D15	4,788	4,788	0	2,077	2,077	0
D16	303	253	-16.4	1,136	949	-16.4
D17	470	470	0	630	630	0
D18	6,458	6,458	0	4,239	4,239	0
D19	168	168	0	1,075	1,075	0
D20	1,507	739	-51.0	5,349	2,622	-51.0
D21	4,486	3,597	-19.8	3,553	2,849	-19.8
D22	4,701	4,081	-13.2	2,928	2,636	-10.0
D23	1,643	1,565	-4.8	1,517	1,445	-4.8
D24	10,421	6,247	-40.1	17,136	10,272	-40.1

Scale Efficiency and RTS analysis

<Table 6> summarizes SE, cause of inefficiency, and RTS. In terms of the production relationship between input and output factors, the efficiency according to optimization can be examined in terms of the scale related to the production capacity of the production entity, which is called scale efficiency (SE). Scale efficiency can be calculated by dividing the technical efficiency, which is the efficiency of the CCR model, by the pure technical efficiency, which is the efficiency of the BCC model (<Table 6>).

If SE is 1, it is a complete scale optimization, and if PTE>SE, the cause of inefficiency is SE, and if PTE<SE, the cause of inefficiency is PTE. It was analyzed that there were 12 DMUs that were IRS, 9 DMUs that were CRS, and 3 DMUs that were DRS.

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	0.847	0.920	0.921	o		IRS
D02	0.183	0.184	0.991	o		IRS
D03	0.697	0.735	0.948	o		IRS
D04	0.768	1	0.768		o	IRS
D05	0.435	0.520	0.837	o		IRS
D06	0.432	0.901	0.480		o	IRS
D07	0.492	0.560	0.878	o		IRS
D08	1	1	1			CRS
D09	0.840	1	0.840		o	DRS
D10	0.651	0.8470	0.768		o	DRD
D11	0.935	1	0.935		o	IRS
D12	1	1	1			CRS
D13	1	1	1			CRS
D14	1	1	1			CRS
D15	1	1	1			CRS
D16	0.5892	0.836	0.705		o	IRS
D17	1	1	1			CRS
D18	1	1	1			CRS
D19	0.557	1	0.557		o	IRS
D20	0.455	0.490	0.929	o		IRS
D21	0.770	0.802	0.961	o		CRS
D22	0.844	0.900	0.937	o		IRS

D23	0.926	0.952	0.973	o		CRS
D24	0.421	0.599	0.702	o		DRS

CONCLUSION

This study was conducted as a measure to respond to the paradigm shift in the fashion industry and improve corporate management efficiency after the COVID-19 pandemic. Input and output factors were selected for 24 fashion companies. These factors were obtained from the financial statements of companies disclosed to the Korea Exchange in 2023, and input factors were selected as debt and capital, and output factors were selected as sales and operating profit.

The DEA methodology was used for efficiency analysis, and the CCR-I model and BCC-I model were adopted for technical efficiency and pure technical efficiency analysis. The evaluation and analysis contents were as follows: First, the relative efficiency of 24 companies was calculated and ranked to distinguish efficient and inefficient companies. Second, the reference set and reference count were analyzed to enable inefficient companies to find efficient companies to benchmark, and the method of calculating the target value for input improvement was shown. Third, the cause of inefficiency of inefficient companies was identified through SE analysis, and the status of companies was diagnosed and responded to increase efficiency through RTS.

This study is meaningful in that it empirically demonstrates a process that can help increase the competitiveness of the fashion industry, and it is expected that the process will be utilized. Furthermore, research is needed to compare and analyze trends in corporate efficiency on an ongoing and periodic basis.

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REFERENCES

Agarwal S., Yadav S. P. & Singh S. (2010). DEA Based Estimation of the Technical Efficiency of State Transport Undertakings in India. Opsearch, 47 (3), 216-230.

Banker, R. D., Charnes, A. & Cooper W. W. (1984). Some Models for Estimating technical and Scale Efficiencies in Data Envelopment Analysis. Management Science, 30, 1078-1092.

Bhagavath V. (2006). Technical Efficiency Measurement by Data Envelopment Analysis: An Application in Transportation. Alliance Journal of Business Research, 2(1), 60-72.

Charnes, A., Cooper, W. W. & Rhodes, E. (1978). Evaluating Program and managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through. Management Science, 27(6), 668-697.

Farrell, M. J. (1957). The Measurement of productivity efficiency. Journal of the Royal Statistical Society. 120(3), 253-290.

Ju, S. H., Lee, S. Y. & Kim, Y. J. (2008). An Empirical Analysis on the Technical Efficiency from the Perspective of Space Closeness in Apparel Textile Industry of Busan. International Area Studies Review, 12(3), 341-365.

Jung, S. H. (2020). The impact of COVID-19 on the textile and fashion industry and its response measures. KIET Industrial Economy Review. 25(3), 80-83.

Lee, E. J. & Hong, J. B. (2021). The Efficient Analysis Case of Distribution: Focusing on Company A

Fashion Retail Stores. Journal of The Korean Data Analysis Society. 23(6). 2,863-2,877.
Odeck J. & Alkadi A. (2001). Evaluating Efficiency in the Norwegian Bus Industry Using Data Envelopment Analysis. Transportation, 28(3), 211-232.
Park, M. H. (2017). A Study on Discrimination Evaluation of DEA Models. The Journal of the Korea Contents association, 17(1), 201-212.
Ryu, E. J., Lee, G. S. & Ahn, M. G. (2023). An Effect of Operating Efficiency and Marketing Activities on CSR Performance of Fashion Corporate, Journal of Taxation and Accounting , 24(1), 9-31.
Shin. Y. G. & Kang, S. M. (2021). Measurement and Decomposition of Cost Efficiency in Fashion Industry: Based on the Directional Distance Function. Productivity Research: An International Interdisciplinary Journal, 35(3), 111-133.