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# Evaluation of Competitiveness of Domestic Aircraft Manufacturing Enterprises Using Data Mining Techniques

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**Abstract**

The global aircraft-manufacturing industry ecosystem is characterized by the international division of labor through the worldwide supply chain and by the concentration of value added at the top of the supply chain. As a result, the competition for entry into the top supply chain and for order expansion is becoming increasingly intensive. To increase their orders, domestic aircraft manufacturing enterprises need to enhance their competitiveness by evaluating and analyzing it. However, most domestic aircraft manufacturing companies are unaware of the need to quantitatively evaluate their competitiveness. It is challenging to perform such an evaluation, and there are few research cases. In this study, we quantitatively evaluated and analyzed the competitiveness of domestic aircraft manufacturers by using data mining techniques. Thereby, implications for enhancing their competitiveness could be identified.

**Key Words:** Aircraft Manufacturing Enterprises, Competitiveness, Data Mining, Feature Extraction, Principal Component Analysis

## 1. Introduction

The global aircraft-manufacturing industry ecosystem is characterized by the international division of labor to achieve price competitiveness through vertical and hierarchical supply chains developed around a small number of aircraft final assembly companies and top-level supply chain companies (tier-1 suppliers). The industry also features the concentration of added value at the top of the supply chain (e.g., Boeing and Airbus).

The third Aerospace Industry Development Master Plan (2021–2030) [1] predicts that 1) the dominance of Airbus and Boeing in the global aviation market would be strengthened further and 2) the demand for price reductions from suppliers and cost competition would intensify owing to China's entry into the market. China is developing domestic civil aircrafts based on the domestic aviation market demand.

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Recently, in the global aviation market, companies that carry out the final assembly of aircrafts have been reshoring the development and production of high value-added applications back to their respective countries. This is aimed at saving development costs, reducing risks, expanding domestic employment, and securing industrial competitiveness. Simultaneously, these companies are expanding the supply chain for low value-added products. As a result, major alterations in the supply structure of the global aviation market is likely, such as an intensification of competition among the top-level supply chain companies and an expansion of the influence of final assembly companies or top-level supply chain companies. Against this background, Price Waterhouse Coopers (PWC; one of the leading credit rating agencies of the world) ranked South Korea as the fourth most attractive aerospace production base country subsequent to COVID-19 (after the United States, Singapore, and Canada). This is considering cost, manpower, infrastructure, related industries, geopolitical risks, economy, and tax system. Therefore, we could expect the domestic aircraft manufacturers to play a role in the reorganization process of the global supply chain in the future.

Domestic aircraft manufacturing enterprises are highly dependent on overseas markets. For these enterprises to grow into aerospace production bases, it is crucial for these to be acknowledged as partners with demonstrated and distinct competitiveness in the global aircraft manufacturing supply chain. Moreover, these need to undertake efforts to evaluate and improve their competitiveness. However, in South Korea, almost no aircraft manufacturer periodically evaluates or analyzes their competitiveness. Furthermore, the concept of competitiveness of aircraft manufacturing enterprises is not defined effectively.

This study selected important factors as indicators for evaluating the competitiveness of domestic aircraft manufacturing enterprises. Then, it analyzed key competitiveness indicators and the current status, conditions, and environment of enterprises that affect these indicators in a complex manner. Finally, this study proposed measures to strengthen the competitiveness of aircraft manufacturing enterprises and to grow the domestic aircraft manufacturing industry.

## 2. Research Trends

All the elements of corporate resources (such as capital, finance, human resources, sales, management, and culture) as well as the factors of production (such as technology, quality, delivery, and price) influence the competitiveness of enterprises in various and complex ways according to their characteristics. Consequently, the method of evaluating the competitiveness of enterprises is also complex and difficult. In South Korea, there are few cases of evaluation and analysis of the competitiveness of the aircraft manufacturing industry and aircraft manufacturing enterprises.

In an overseas case study, Chursin [2] used 12 features to evaluate a company's competitiveness: price competitiveness, cost advantage, product operation characteristics (quality, design, and packaging), after-sales services, speed of response to consumer demand, product image, cooperation with suppliers, scope of distribution network, advertisement, individual sales capabilities, sales information systems, and marketing research. Zhang [3] recommended a system of 20 indices for evaluating the competitiveness of the Chinese aerospace manufacturing industry. These include number of employees, number of patents, total assets, R&D manpower, new product R&D expenditure, main business sales, gross profit, and exports. Zheng [4] presented 16 evaluation indices for the core competitiveness of aerospace companies: percentage of employees who are university graduates or above, percentage of professionals, customer growth rate, advanced core technology, patent ownership, new product projects, collaboration with research institutes, product performance, product quality, market share of products, percentage of contracted companies, corporate technical service conditions, government support for companies, and protection of intellectual property rights.

As shown in the above examples, the indicators for enterprises competitiveness are not standardized. These must be established considering the characteristics and circumstances of the industry.

Based on a review of existing studies and of the order, production, and sales structures of domestic aircraft manufacturing enterprises, this study established the competitiveness indicators of domestic aircraft manufacturing enterprises and designed a system of predictor variables to determine competitiveness. This system was then used to evaluate and analyze competitiveness based on quantitative data.

Public company information portals were used for obtaining data related to competitiveness indicators such as profitability, activity, growth potential, technology, and productivity. In addition, certain private data were obtained directly from the enterprises. These data were analyzed and evaluated using a data mining technique. Finally, we proposed measures for domestic aircraft manufacturing enterprises to increase their competitiveness and secure a competitive edge in the global aircraft manufacturing market.

## 3. Analysis Method

### 3.1 Data mining

Data mining is a process of extracting valuable information by systematically and automatically analyzing statistical rules or patterns from large amounts of stored data. It is a data analysis technique that is also called knowledge-discovery in databases (KDD). The data mining process is largely composed of five steps: (1) selection and sampling to extract data required to obtain results; (2) preprocessing and cleaning to handle incomplete, contradictory, and invalid values; (3) transformation and reduction to identify and remove unnecessary variables through feature extraction while verifying data variables; (4) model building (analysis type, technique, algorithm, and visualization) and application; and (5) interpretation and evaluation to interpret the results of data mining to be used for decision making.

### 3.2 Analysis Process

#### 3.2.1 Data selection

To analyze competitiveness, it is important to determine its indicators and the predictor variables that affect it. Once these are determined, related data must be collected. However, if the data are collected from many sources, there may be problems such as differences in data storage formats, inconsistency in the meanings of items, and missing values. Therefore, the data should be organized to address these issues. Data organization involves the removal of invalid data or complement missing values, determination of hidden correlations of data, and identification of the most appropriate values of data for analysis.

### 3.2.2 Data preprocessing

Data preprocessing includes normalization and outlier handling. Data can commonly be expressed in entirely different scales. As a result, excessively large weights can be assigned to certain variables, whereas others can be relatively omitted. The goal of normalization is to alter the numeric string values of a dataset into a common scale without distorting the differences in the range of variables.

The data that have an abnormal effect on the regression result are called outliers. The effect of each data sample on the regression analysis result can be determined through leverage or outlier analysis. Leverage indicates the effect of the value of a dependent variable on the predicted value. The size of leverage of each data can be identified by comparing a model that includes the data and one that does not. The effect that data with a large leverage has on the model can be assessed by observing whether the data is included in regression analysis or not.

Data that are different from those described by the model (i.e., data with large residuals) are also outliers. In general, the data is considered an outlier if the standardized residual is larger than 2–4. The data of particular interest are those with large leverage and residual. A criterion for viewing both leverage and residual is Cook’s distance. Cook’s distance increases if the leverage or residual increases. The data whose Cook’s Distance is excessively large were removed from the dataset.

### 3.2.3 Feature extraction

Not all features in a data set have the same effect on the output variable. The identification of the features that have a significant effect on the model is called feature extraction. In this study, Lasso (least absolute shrinkage selector operator) regression was used.

In linear regression, to predict the value using Eq. (1), the coefficient $\Omega$ is determined using Eq. (2). This equation minimizes the mean squared error (MSE), which is obtained by squaring the differences between target and predicted values and then, averaging the result.

$$\hat{y} = \omega_0 + \omega_1 x_1 + \cdots + \omega_m x_m = \Omega X^T \tag{1}$$

Here, $m$ is the number of predictor variables, and $n$ is the number of data.

$$\min MSE = \min \frac{1}{n} \sum_{i=1}^{n} (\mathrm{y_i} - \hat{y}_i)^2 \tag{2}$$

Lasso regression adds a constraint to this and then, determines the parameter $\alpha$ that minimizes the following equation:

$$\min\left(MSE + \alpha \sum_{j=1}^{m} |\omega_j|\right) \tag{3}$$

In the case of Lasso regression, the coefficient decreases to zero even for a small value of $\alpha$. Therefore, Lasso regression selects only a few important variables and reduces the other coefficients to zero. The variables that have a large effect on dependent variables are determined using this feature.

### 3.2.4 Principal component analysis (PCA)

PCA is a technique that reduces high-dimensional data to low-dimensional data. It uses orthogonal transformation to transform samples in a high-dimensional space that are likely to be correlated, into samples in a low-dimensional space (principal components) that are not linearly correlated.

The data mapped to an axis are linearly transformed into a new coordinate system so that the axis with the largest variance would become the second principal component. The decomposition of the data to components that best indicate the differences of samples provides various advantages for data analysis. In this study, PCA was performed to identify a combination of predictor variables that cause the largest variation in the dependent variables. This process can be described mathematically as follows.

When a general linear regression equation is expressed as Eq. 1, $X$ is a $(n, m)$ matrix, and $\Omega$ is a $(1, m)$ matrix. Using PCA, $X$ can be expressed as follows:

$$X = \alpha_1 \varphi_1 + \cdots + \alpha_m \varphi_m = \Phi \cdot \alpha \tag{4}$$

where $\Phi = \{\varphi_1, \cdots, \varphi_m\} \in R^{n \times m}$ is a basis vector, $\alpha = \{\alpha_1, \cdots, \alpha_m\} \in R^m$ is a principle component decomposition coefficient or a singular value.

The data deviation matrix $p$ can be expressed as follows:

$$p = (X_1 - \bar{X}, X_2 - \bar{X}, \cdots, X_m - \bar{X}) \tag{5}$$

where the average value of the snapshot vector is $\bar{X} = \frac{1}{M} \sum_{j=1}^{m} X_j$.

The following equation can be obtained by performing singular value decomposition for the snapshot deviation vector:

$$p = U \sum V^T = U \begin{bmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_m \\ 0 & \cdots & 0 \end{bmatrix} V^T \tag{6}$$

where $\mathrm{U} \in R^{n \times n}$ and $\mathrm{V} \in R^{m \times m}$. $\sigma_1 \geq \sigma \geq \cdots \geq \sigma_m \geq 0$ are singular values. The $m$ rows of the matrix $U$ constitute the basis vector $\varphi$. The singular value decomposition coefficient $\alpha_i$ is obtained by projecting the data vector onto the basis vector as follows:

$$\alpha_i = (X_j - \bar{X},\ \varphi_i) \tag{7}$$

The approximate value of the snapshot vector with a decreasing order can be expressed as follows:

$$\hat{X}_j \cong \bar{X} + \sum_{i=1}^{\hat{m}} \alpha_i \varphi_i \tag{8}$$

where $\hat{m}$ is the selected reduction order.

## 4. Evaluation of Competitiveness of Aircraft Manufacturing Enterprises

The competitiveness of domestic aircraft manufacturing enterprises was evaluated by applying the data mining analysis process to the data of the enterprises.

### 4.1 Status of domestic aircraft manufacturing enterprises

In the domestic aircraft manufacturing industry, over 120 companies participate directly and indirectly in the global aircraft manufacturing supply chain. These include Korea Aerospace Industries (KAI; manufactures civil aircraft components and military aircraft systems), Korean Air (Tech Center; focuses mainly on airframe structures and depot maintenance), Hanwha Aerospace (specializes in engine), Hanwha Machinery (specializes in hydraulic systems), WIA (specializes in landing gears), and LIG Nex1 and Hanwha Systems (specializes in avionics). As of 2020, the total number of employees in the domestic aerospace industry was 17,283. This is 1.7% lower than that in the previous year (17,574). The reduction is a result of COVID-19 [5].

In this study, the competitiveness of 48 domestic companies participating in aircraft manufacturing were evaluated. These include 1) companies with a high proportion of aircraft production and 50 or more full-time employees, and 2) those with less than 50 full-time employees but whose aviation sales account for more than 90% of total sales. The companies with large leverage and residual were excluded from the regression analysis process. The competitiveness indicators of the 46 finally selected companies were quantitatively evaluated and analyzed.

### 4.2 Data selection

To evaluate the competitiveness of domestic aircraft manufacturing enterprises, competitiveness indicators must first be established. Then, a system of predictor variables that influence competitiveness must be designed. Subsequently, the data regarding competitiveness indicators and predictor variables must be collected, analyzed, and evaluated.

On the one hand, a previous study defined the competitiveness indicators of an enterprise as integrated indicators that reflect the capability to produce competitive products. On the other hand, these are defined as economic, technological, and other business characteristic indicators [2]. Based on the indicators proposed by previous studies and a review of the process of sales creation through order, production, and sales of domestic aircraft manufacturing enterprises, this study set sales volume as the competitiveness indicator. This is because the competitiveness of a company finally materializes as sales. For competitiveness analysis, it is crucial to determine the predictor variables that influence competitiveness. The process of determining the degree of influence of each predictor variable on competitiveness, removing the predictor variable that has no influence, and adding a new predictor was performed repeatedly.

The competitiveness of domestic aircraft manufacturing enterprises is influenced in a complex manner by various indicators including purchasing related factors such as quality, price, and delivery time; manufacturing resources related factors such as sales, management, technology, personnel, buildings, facilities, and equipment; corporate culture; growth potential; and financial related factors such as profitability, financial stability, financial activity, and productivity. This study finally selected 18 variables after collecting data of predictor variables that can influence sales volume (Table 1). The selection was based on the financial statements published by the companies and data directly surveyed. Furthermore, variables that showed little influence in data mining analysis was deleted. The competitiveness of the selected companies was evaluated and analyzed using these predictor variables.

**Table 1** Predictor Variables for Competitiveness Analysis

| No ($x$) | Predictor variables | Unit | Collecting method |
|---|---|---|---|
| 1 | Business experience | year | cretop |
| 2 | Number of full-time workers | person | cretop |
| 3 | Research and production technology personnel | person | direct survey |
| 4 | University graduates or above | person | direct survey |
| 5 | Industrial property rights | number | cretop |
| 6 | Factory scale | ㎡ | direct survey |
| 7 | Total assets | million KRW | cretop |
| 8 | Current ratio | % | cretop |
| 9 | Debt ratio | % | cretop |
| 10 | Value-added ratio | % | cretop |
| 11 | Exports | 100 million KRW | direct survey |
| 12 | Operating profit margin | % | cretop |
| 13 | Military share | % | direct survey |

| | | | |
|---|---|---|---|
| 14 | Sales-to-labor ratio | % | cretop |
| 15 | Capital adequacy ratio | % | cretop |
| 16 | Equipment investment efficiency | % | cretop |
| 17 | Gross value-added to total assets | % | cretop |
| 18 | Sales-to R&D ratio | % | cretop |

The data required for analysis were obtained mainly from Cretop (www.cretop.co.kr). It is the largest Internet-based credit assessment service in South Korea that provides company credit information, venture business information, consumer credit information, and various types of economic information. Cretop has been constructed by Korea Enterprise Data [6] through company credit research. Other essential data were obtained by direct survey and other methods. Missing values were not processed because all the data could be secured.

Among the 18 predictor variables required for analyzing the competitiveness of domestic aircraft manufacturing enterprises, the data for 13 were collected from Cretop. These included business experience, number of full-time workers, industrial property rights, total assets, current ratio, debt ratio, value-added ratio, operating profit margin, sales-to-labor ratio, capital adequacy ratio, equipment investment efficiency, gross value-added to total assets, and sales-to-R&D ratio. In addition, the data for five predictor variables including research and production technology personnel, university graduates or higher, factory scale, exports, and military share were collected through direct survey.

### 4.3 Data preprocessing

The data in Table 1 were normalized with zero and one as the minimum and maximum values, respectively. Cook's Distances for the data of all the 48 companies were extracted using the influence_plot of statsmodels [7] as shown in Fig. 1. In this figure, Cook's Distance is indicated by the bubble size. The data of companies 45 and 46 were excluded because these were outliers compared with the data of other companies. Fig. 2 shows the leverages and residuals for outliers.

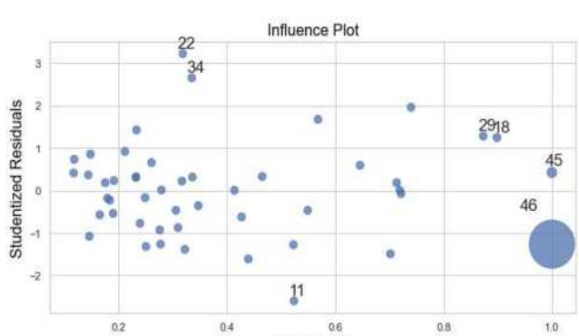


**Fig. 1** Cook's Distance for Industry Data

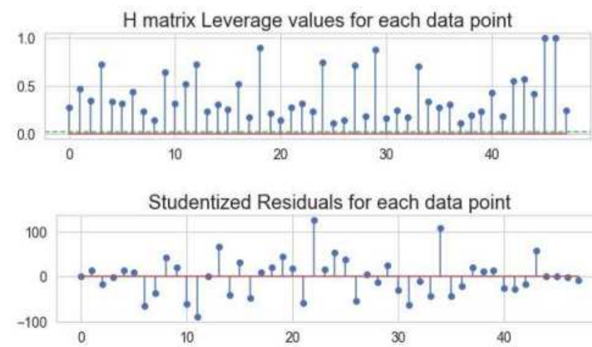


**Fig. 2** Leverage and Residuals for Industry Data

### 4.4 Feature extraction

Linear regression was performed on the data of the 46 domestic aircraft manufacturing enterprises. $R^2_{adj} = 0.933$ was obtained. This indicates that the linear relationships of predictor variables and competitiveness indicators can be explained sufficiently. The Lasso analysis result obtained using scikit-learn [8] is shown in Fig. 3. As shown in this figure, the predictor variable that had the highest effect on competitiveness was number of full-time workers ($x_2$). It was followed by exports ($x_{11}$), total assets ($x_7$), and research and production technology personnel ($x_3$) in that order.

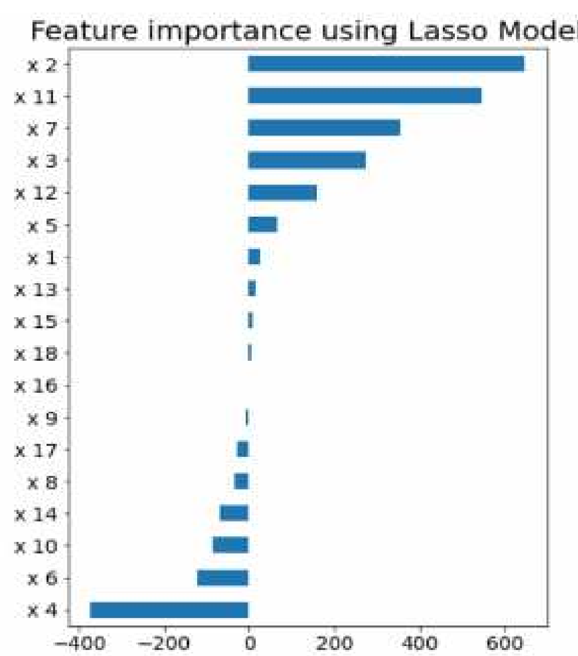


**Fig. 3** Lasso analysis for linear regression

### 4.5 PCA analysis result

The basis vectors $\varphi_1 - \varphi_{18}$ were obtained by performing PCA with the data of the 46 companies. The competitiveness indicator $\hat{y}$ can be expressed by linear equations (Eqs. 9 and

10) in $X$ (predictor variable) and $\varphi$ (basis vector), respectively. The regression coefficients $\omega$ and $\beta$ are listed in Table 2.

$$\hat{y} = \omega_0 + \omega_1 x_1 + \cdots + \omega_m x_m = \Omega X^T \quad (9)$$

$$\hat{y} = \beta_0 + \beta_1 \varphi_1 + \beta_2 \varphi_2 + \cdots + \beta_{18} \varphi_{18} \quad (10)$$

Table 2 shows that the competitiveness indicators react more intensively to predictor variables than to basis vectors. The descending order of sensitivity is $x_2$, $x_{11}$, $x_3$, $x_7$, $x_{12}$, and $x_5$. It can be observed that competitiveness can be developed most rapidly by increasing the number of full-time workers, exports, research and production technology personnel, total assets, operating profit margin, and industrial property rights.

**Table 2** Regression Coefficients

| $\omega$ | Regression coefficient | Sensitivity ranking | $\beta$ | Regression coefficient | Sensitivity ranking |
|---|---|---|---|---|---|
| $\omega_0$ | 9.264 | | $\beta_0$ | 227.372 | |
| $\omega_1$ | -7.263 | 22 | $\beta_1$ | 81.165 | 7 |
| $\omega_2$ | 889.661 | 1 | $\beta_2$ | 41.281 | 9 |
| $\omega_3$ | 317.211 | 3 | $\beta_3$ | 24.065 | 15 |
| $\omega_4$ | -611.078 | 36 | $\beta_4$ | -24.176 | 26 |
| $\omega_5$ | 82.812 | 6 | $\beta_5$ | 24.711 | 14 |
| $\omega_6$ | -172.117 | 34 | $\beta_6$ | -37.550 | 28 |
| $\omega_7$ | 257.276 | 4 | $\beta_7$ | 16.098 | 17 |
| $\omega_8$ | -55.404 | 30 | $\beta_8$ | 48.209 | 8 |
| $\omega_9$ | 7.751 | 19 | $\beta_9$ | 24.749 | 13 |
| $\omega_{10}$ | -102.018 | 32 | $\beta_{10}$ | -17.859 | 24 |
| $\omega_{11}$ | 628.344 | 2 | $\beta_{11}$ | -29.604 | 27 |
| $\omega_{12}$ | 213.410 | 5 | $\beta_{12}$ | 20.147 | 16 |
| $\omega_{13}$ | 8.583 | 18 | $\beta_{13}$ | -10.259 | 23 |
| $\omega_{14}$ | -54.646 | 29 | $\beta_{14}$ | -2.900 | 21 |
| $\omega_{15}$ | 37.769 | 10 | $\beta_{15}$ | -1.783 | 20 |
| $\omega_{16}$ | 29.145 | 12 | $\beta_{16}$ | -21.720 | 25 |
| $\omega_{17}$ | -114.853 | 33 | $\beta_{17}$ | -85.295 | 31 |
| $\omega_{18}$ | 35.374 | 11 | $\beta_{18}$ | -217.086 | 35 |

### 4.6 Interpretation of analysis results

It can be observed that number of full-time workers ($x_5$), exports ($x_{11}$), research and production technology personnel ($x_3$), total assets ($x_7$), and operating profit margin ($x_{12}$) must be increased to improve the competitiveness of domestic aircraft manufacturing enterprises. Thus, the large values of number of full-time workers, exports, and total assets indicate that the size of an aircraft manufacturing enterprise has a significant influence on competitiveness. In particular, number of full-time workers and exports have exceptionally high sensitivity. This indicates that although the domestic aircraft manufacturing process is centered on processing and assembly, it has an industrial characteristic that promotes employment. This is because it is difficult to automate the process compared with other industries. Furthermore, the domestic aircraft manufacturing industry is export-oriented and depends on overseas orders for all components of civil aircrafts. Its competitiveness is affected substantially by exports. The next most sensitive was research and production technology personnel. This is because research and production technology personnel have a significant effect on competitiveness. They are required for aircraft design, process design, manufacturing capability, equipment, manpower, customer certification and maintenance, and tool design for the aircraft manufacturing enterprises to participate in component manufacturing. Total assets have the fourth highest sensitivity. This is because the scale of assets must be relatively large for aircraft manufacturing enterprises to have competitiveness: the manufacturing of aircraft components requires the construction of advanced facilities and equipment. The variable with the fifth highest sensitivity is operating profit margin. It shows the characteristic of economies-of-scale, where the average cost decreases and profits increase as production increases with large total assets. Furthermore, it was verified through quantitative analysis that companies having many research and production technology personnel and many industrial property rights through active R&D activities have a competitive edge.

In contrast, university graduates or above ($x_4$), sales-to-R&D ratio ($x_{18}$), and factory scale ($x_6$) show the highest negative sensitivity values in this order. This is because the employment of candidates with university graduates or above is becoming more common in the aircraft manufacturing industry. Furthermore, there are a small number of companies with low sales and high R&D ratio. In addition, it was observed that the factory scale had a relatively significant effect on competitiveness for certain companies participating in the assembly aircraft structures, although their sales were small. As shown through this sensitivity analysis, variables that denote the size of the company (such as number of full-time workers, exports, total assets, and operating profit margin) and technical competencies (such as research and production technology personnel and industrial property rights) have a significantly large effect on the competitiveness of domestic aircraft manufacturing enterprises.

The domestic aircraft market has a highly limited size notwithstanding the ongoing development and mass production of a small number of military aircraft platforms. It does not have a domestic civil aircraft platform. In contrast, the volume of commercial aircrafts in the global aircraft manufacturing market accounts for approximately 80%. The domestic aircraft manufacturing industry is maintaining its foundation by achieving its civil aircraft manufacturing volume through overseas orders. Therefore, the competitiveness of domestic aircraft manufacturing enterprises is in the form of export competitiveness. Hence, the key to the competitiveness of the domestic aircraft manufacturing industry lies in the fostering of large-scale aircraft manufacturing enterprises that have 1) the competitive capability to obtain overseas orders and thereby overcome the limitations of the domestic market and 2) the scale that can produce and deliver orders in a timely manner. To summarize, various order support strategies for domestic aircraft manufacturing enterprises to realize economies-of-scale by expanding orders, and sustainable development policies that can enhance price and technological competitiveness are required for the ecosystem of the domestic aircraft manufacturing industry to achieve competitiveness.

## 5. Conclusions

The competitiveness of domestic aircraft manufacturing enterprises was analyzed quantitatively using a data mining technique. The result showed that it is most necessary to realize economies-of-scale based on technology (e.g., growth, orders, production, supply capabilities, research and production technology, operating profit margin, and industrial property rights), in terms of company size (e.g., number of full-time workers, exports, and total assets). To improve the accuracy of the competitiveness evaluation of aircraft manufacturing enterprises, we require more predictor variables and corporate data. However, among the domestic aircraft manufacturing enterprises, the aviation sales accounts of approximately 100 companies account for over 50% of their total sales. Among these, only 50 companies employed 50 or more full-time workers. Of these 50 companies, 46 were finally analyzed after excluding those having datasets with particularly large data deviations. The analysis was performed based on 18 predictor variables owing to the limitations on obtaining data on certain product characteristics such as quality and delivery time. As a result, the data were insufficient for improving the accuracy of competitiveness evaluation. Therefore, to improve competitiveness, research and analysis on additional factors by using additional datasets is required in conjunction with the introduction of smart factories by aircraft manufacturing enterprises (which have been actively carried out recently).

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