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Determining Factors Influencing Short-Term International Aviation Traffic Demand Using SHAP Analysis: Before COVID-19 and Now

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Abstract: Due to the COVID-19 outbreak, international aviation travel has declined globally to the level it was 30 years ago. Influencing factors are explored to understand the difference in short-term international aviation travel demand before and after the COVID-19 pandemic. SHapley Additive exPlanations (SHAP), an exploratory data analysis methodology, is applied to identify the factors affecting aviation demand. Daily international aviation passenger volume data (1462 in total) between 2018 and 2021 are analyzed with 10 socioeconomic variables and the number of daily confirmed COVID-19 cases in Korea. It was found that the number of confirmed cases did not have the greatest direct influence on the short-term demand for international demand, but it has a strong correlation with socioeconomic factors. This study's findings on the factors influencing short-term international air passenger demand from a macro perspective will contribute to demand forecasting after COVID-19. It is expected that this research can be applied to other countries or other pandemic data to investigate the post-pandemic demand changes.

Keywords: aviation traffic demand; influencing factors on demand; SHAP analysis; Shapley value; big data analysis

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Citation: Song, K.-H.; Choi, S.; Elkosantini, S.; Suh, W. Determining Factors Influencing Short-Term International Aviation Traffic Demand Using SHAP Analysis: Before COVID-19 and Now. *Sustainability* **2023**, *15*, 14924. https://doi.org/10.3390/su152014924

Academic Editors: Wen-Hsiang Hsieh and Jia-Shing Sheu

Received: 29 August 2023
Revised: 6 October 2023
Accepted: 7 October 2023
Published: 16 October 2023

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1. Introduction

Influencing factors are explored to understand the difference in short-term international aviation travel demand before and after the COVID-19 pandemic. Exploratory data analysis is utilized to classify influencing factors before and after the COVID-19 outbreak. It is known that certain variables have a significant influence on air travel demand [1,2], and existing studies rely primarily on confirmatory data analysis. Confirmatory data analysis has the advantage of a theoretical system because it verifies hypotheses in a rigorous and systematic manner, but it is difficult to identify new patterns. Particularly in the present environment, where future uncertainty is deepening, there is a limit to identifying the factors that influence short-term demand and identifying concealed relationships. In addition, since the COVID-19 outbreak, user behavior and industrial structure have changed, making it more challenging to ascertain the factors that influence short-term international air passenger demand. Using SHapley Additive exPlanations (SHAP) analysis, a method for exploratory data analyses, the factors influencing short-term international air passenger demand are examined [3].

It is well-known that short-term economic indicators and exchange rates influence both air travel demand factors (e.g., passengers, tariffs, convenience-related factors) and supply factors (e.g., traffic rights, infrastructure, slot-related factors) [4–8]. Even during the COVID-19 pandemic, it was possible to predict that such external factors would influence short-term air travel demand; however, this study began with the assumption that the level and manner in which individual indicators affect demand would be different than before the pandemic. Exploratory data analysis was conducted using SHAP analysis [9,10] to identify external influences and observe changes, rather than confirmatory data analysis, which identifies factors such as the correlation or causality between short-term demand and independent variables. In addition to the factors presented in previous studies, we analyzed all measurable variables estimated to affect air travel demand in an attempt to avoid potential biases such as confirmation bias and hindsight bias.

As the social economy evolves rapidly, there is a growing importance of short-term air travel demand forecasting in establishing and implementing government policies, operating airlines and terminals, and aircraft manufacturers making strategic decisions. Trend-based time-series analysis is limited in its ability to reflect the rapidly changing environment, and there may be insufficient evidence to reflect the rapidly changing environment as a scenario. To address this issue, it is necessary to comprehend the factors that influence the short-term demand for international flights. Existing research on this topic is available [11,12], but it is reasonable to presume that other mechanisms will operate during the COVID-19 pandemic. Influencing factors may also change after the pandemic comes to an end; however, we may be able to prepare in advance for future pandemic situations by identifying the influencing factors in the COVID-19 situation.

In Section 2, studies pertaining to factors influencing short-term international air passenger demand and SHAP analysis are reviewed. Section 3 presents the methodology for exploratory factor analysis in detail. In Section 4, a comparative analysis is performed, and the pre- and post-COVID-19 impacts and levels are analyzed. Finally, discussions and conclusions are proposed in Section 5.

This study aims to examine the alterations in factors pertinent to the aviation industry in South Korea both prior to and in the wake of the pandemic. To substantiate our findings empirically, we employed machine learning modeling techniques and conducted an importance assessment utilizing socioeconomic variables. These analytical approaches allowed us to derive more nuanced and exploratory research outcomes.

2. Literature Review

Socioeconomic variables have frequently been used as demand forecasting factors. Ref. [13] defined a demand forecasting methodology as a demand derivative for general economic conditions by using GDP as an air travel demand factor. In addition, Ref. [14] demonstrated that global air traffic increased by 1.58% for every 1% increase in GDP. Totamane, R., Dasgupta, A., and Rao, S. (2012) [15] used demand forecasting influencing factors for policy variables and service/supply variables as an auxiliary, employing capacity as a supply variable as a predictor to demonstrate the effect of each cargo plan in order to predict cargo load factors for flight schedules (that is, air cargo demand forecasting). Contingent variables, on the other hand, have been utilized for influencing factors and demand forecast analysis utilizing disease-associated variables (e.g., severe acute respiratory syndrome, Middle East respiratory syndrome (MERS)) that had a significant impact on the decline of the aviation industry, including the recent COVID-19. Ref. [16] attempted to quantify the specific impact of MERS on the Korean domestic airline and inbound tourism markets. Consequently, Ref. [16] demonstrated that it was statistically significant that infectious diseases had negative effects among inbound visitors during the MERS outbreak, necessitating a quantitative experiment on the establishment of relevant policies.

Detailed forecasts (correlation and causality) by year or month have been employed in the above-mentioned study on the significance and predictive analysis of air travel demand's influencing factors. However, in the current situation, where the impact of COVID-19 is pervasive, the need for research on two research questions becomes apparent. The first question is, "How has the significance of the factors influencing air travel demand changed since the upheaval due to COVID-19?" The second question is, "How do microscopic analysis results, such as daily demand for representative variables, manifest themselves in the present with multi-criteria data-based analysis algorithms such as big data and artificial intelligence analysis?" Identifying and predicting significant factors in air travel demand can be carried out on the basis of air travel demand time-series data by year and month. However, they have limitations in terms of securing the optimal number of data samples and determining the structure of each influencing factor in the complex aviation industry. This study, therefore, uses the SHAP methodology, which is an algorithm for explaining the output of a machine learning (ML) model, to distinguish data-based multi-criteria influencing factors.

In this study, we employed SHAP (SHapley Additive exPlanations) as a tool to validate both the practical and theoretical aspects of our research. SHAP provides a framework to elucidate the results of our machine learning model by attributing the contributions of each factor to the model's output, starting from the baseline values of explanatory variables. In essence, SHAP values serve as indicators of the reliability of individual features in influencing changes in the model's output. They help distinguish features that bolster higher predictions from those that lead to lower predictions.

The SHAP methodology is defined by an algorithm based on the Shapley value of game theory, which can determine the influence of variables on the predicted values of ML models (e.g., XGBoost) and the degree to which predicted values change as a result of input variables (explaining ML model output) [17]. In the SHAP methodology, models that can be explained separately are constructed based on the learning data and the learned model, and the Shapley value, which expresses the direction and magnitude of the newly input data's degree of influence on the prediction, is calculated. Therefore, it can measure the influence more precisely than the variable importance selection technique currently applied to air travel demand [17]. It is also possible to interpret which input variable has high importance and how the predicted value changes according to the newly input variable [17].

Using SHAP, significant social and economic factors and relationships have been identified in greater detail. In the study conducted by CHANG, [18], both XGBoost and SHAP were used to investigate the relationship between physical factors and pedestrian fatalities at the level of location and to identify the relationship between related functions and pedestrian fatality risk. Using the above SHAP analysis results, transportation and urban planning engineers were introduced with policy proposals to increase the density of nearby residential and commercial land use. Ref. [19] used SHAP analysis to estimate the spatial effects of complex geographic phenomena and processes and interpret vehicle demand in Chicago locally, whereas [20] attempted to analyze the characteristics and significance of each factor by incorporating ML techniques—XGBoost and SHAP—into traffic collision data collected from highways in the Chicago metropolitan area. As a result, it was determined that traffic-related characteristics, particularly the difference in speed between five minutes before and after a collision, had a relatively greater influence on the occurrence of traffic collisions.

In addition, research on the industrial application of SHAP has been conducted. Ref. [21], for instance, created an industrial accident prediction model for all industries to reduce domestic industrial disaster problems using SHAP and the LightGBM model, and the influence of Shapley values by variable was visualized. Their study interpreted the "existence of risk mechanisms" as having the greatest negative influence (−) on the occurrence of industrial disasters. Ref. [22] acknowledged the need for research into which global pandemic-related variables should be considered when predicting airport passenger trends in response to the COVID-19 outbreak, and they conducted daily correlation analyses between COVID-19 pandemic trends and air passenger traffic in China's main airport terminals. Ref. [22] categorized air passenger change during the COVID-19 outbreak into three stages (reduction, stabilization, and recovery) and utilized SHAP in order to quantify the contribution of input variables based on daily passenger traffic using the LightGBM model. As a result, sophisticated forecasting-based countermeasures were proposed for airport terminal operations in response to the COVID-19 pandemic.

To test the research hypotheses, we utilized the SHAP methodology to examine how the air travel demand-affecting variables changed before and after COVID-19. To achieve this, a comparative analysis of the two time periods was conducted using the aforementioned variables and methodology.

3. Methodology

To extract the significance of air passenger demand using SHAP analysis [23,24], air passengers were designated as input variables to the LightGBM ensemble model [25]. In addition, a research model for measuring performance was configured with the stock price, exchange rate, and socioeconomic variables set as learning data. We divided the time points for each model into two years before the COVID-19 pandemic (2018–2019), two years following the outbreak (2020–2021), and the entire period (2018–2021), and then input the daily data for each period (with monthly data among socioeconomic variables applied in bulk on a daily basis). Using the derived SHAP feature importance values, we conducted a paired sample verification by group to validate whether the features that were visible before and after the pandemic appeared independently (Figure 1).

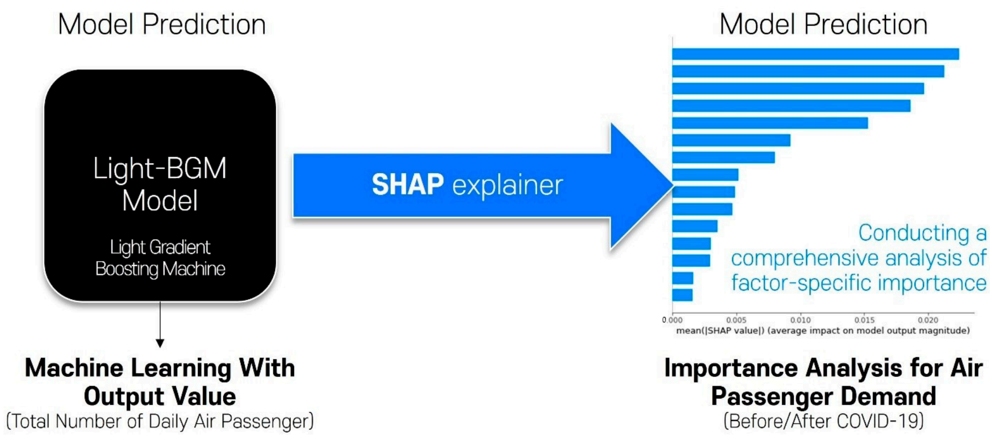

Figure 1. Analysis process.

3.1. Dataset

In the case of the datasets presented in this study, passenger data from the Korean aviation industry's tower-log data were extracted, particularly daily passenger data (1462 in total) between 2018 and 2021. Indicators set as socioeconomic variables include exchange rates (KRW/USD, KRW/CNY, KRW/JPY 100, and KRW/EUR), stock market indices [total indices of the Korea Composite Stock Price Index (KOSPI) and the Korea Securities Dealers Automated Quotation (KOSDAQ)], and economic indicators (composite indices of leading indicators, coincident indicators, and lagging indicators). In addition, we input the number of daily confirmed COVID-19 cases in Korea as an event variable to validate the significance after the pandemic. We divided each data cluster into three sections: two years before the pandemic (2018–2019, daily data), two years after the pandemic (2020–2021), and two years of datasets with daily confirmed cases. We determined the significance of socioeconomic and event variables for air passenger demand for each period and examined the differences between responding groups.

In the case of exchange rates, we utilized the notices published by the Seoul Money Brokerage Services to determine the daily exchange rates of major currencies (KRW/USD, KRW/CNY, KRW/JPY 100, and KRW/EUR). In terms of stock market index data, we used the "KOSPI index" and the "KOSDAQ index" as input data to represent domestic macroeconomic trends. If the foreign exchange market or stock market was closed due to a holiday, the data were adjusted to reflect the previous trading day. The composite index of leading indicators is an economic indicator comprised of 10 indicators (including the inventory cycle index, consumer confidence index, and machine order quantity) that vary prior to the actual business cycle. The composite index of coincident indicators is an index that reflects the current state of the economy and can be defined as an index comprised of seven major indices (e.g., mining industry production index, service industry production index, consumption sales index). The composite index of lagging indicators can be defined as a combination of five indicators (e.g., inventory index, consumption expenditure) that vary according to the actual business cycle and have the property of confirming the previous economy ex post facto. Since these economic indices are monthly data, we modified the daily index values and used them as input variables in this study.

3.2. Shapley Value

The Shapley value, which is the foundation of SHAP analysis, is a formula based on game theory that calculates the contribution of each participant in a game. It refers to a value derived from the average change in the presence or absence of a combination of several features to determine the significance of one feature [26]. The formula for the final Shapley value is represented as follows [27].

$$\phi_i = \sum_{S \subseteq F \setminus i} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f_{S \cup i}(x_{S \cup i}) - f_S(x_S)] \quad (1)$$

ϕ_i = i The Shapley value for data; F = Complete set; S = All remaining subsets of the complete set excluding the ith data; $f_{S \cup i}(x_{S \cup i})$ = Total contribution including the ith data; $f_S(x_S)$ = Contribution of the remaining subsets excluding the ith data.

The Shapley value has the following four characteristics, and the corresponding formula is as follows [27].

$$\sum_{j-1}^{p} \phi_j = \hat{f}(x) - E_x(\hat{f}(X)) \quad (2)$$

Efficiency: The sum of each feature's contributions is expressed as the difference between the predicted value for x and the average.

$$f(S \cup \{x_j\}) - f(S \cup \{x_k\}) \quad (3a)$$

$$\phi_j - \phi_k \quad (3b)$$

Symmetry: The contributions of the two features j and k must be equal if they contribute equally to all possible coalitions.

$$f(S \cup \{x_i\}) = f(S) \quad (4a)$$

$$\phi_j = 0 \quad (4b)$$

Dummy: The Shapley value equals 0 for feature j, which does not affect the predicted value.

$$\phi_j + \phi_j^+ \quad (5)$$

Additive: The Shapley value derived from the function value obtained by adding the function values f and f+ from each game is equal to the sum of each game's Shapley values.

3.3. SHAP (SHapley Additive exPlanations)

In SHAP analysis, the SHAP values are calculated for each input variable in order to investigate the relationship between the input variable and the model's output value. The SHAP values are defined as the Shapley values for the ML model's conditional expected value function. In game theory, the Shapley value refers to a value distributed proportionally to the contribution of participants from all profits obtained through cooperation among game participants. The above ML model includes a feature that indicates the significance of an input variable by comparing the expected value for the input value to the expected value for the model without a particular input variable [23]. Therefore, when the ML model is analyzed using SHAP, it is determined that multiple interpretations are possible regarding which input variable has a high degree of significance and how the expected value changes when the input variable's value changes.

SHAP analysis is also an ML methodology that can interpret the black box of ML models. As a game-theory-based methodology to explain the contribution of all ML models [23], the contribution of the Shapley values is split into two parts: the global Shapley values and the local Shapley values. In the case of the global Shapley values, they are enumerated in ascending order according to the magnitude of the influence. They are represented in red if the aggregate influence is positive and in blue if it is negative. In the case of the local Shapley values, the contribution of variables is illustrated using a density scatterplot, where each point represents a single piece of data. The colors of each point represent the actual value of the variable. Red means high variable value and blue means low variable value. If a variable is displayed on the right as the value increases, it has a positive relationship with air passenger demand. If it is displayed on the left, it means it has a negative relationship.

In this study, the LightGBM model was used as an ML model to apply the comprehensive SHAP analysis described above. As an ensemble model employing a boosting algorithm, the LightGBM model has become increasingly popular due to its high accuracy and rapid learning rate [25]. The model sequentially learns multiple classifiers as a method for integrating several weak models to create a more accurate and powerful model. Because it has the property of reducing errors by allocating weights to incorrectly predicted data in the previous model, we used the LightGBM model to determine the precise influence of socioeconomic variables on air passenger demand.

4. Results and Discussion

Figure 2a,b illustrates the significance of air passengers to SHAP for a total of 10 variables before the pandemic (2018–2019). In the SHAP analysis results before the pandemic, the price index had the highest Shapley values, followed by KRW/JPY 100, the composite index of coincident indicators, KRW/CNY, the KOSDAQ index, KRW/EUR, the KOSPI index, KRW/USD, the composite index of lagging indicators, and the composite index of leading indicators. In the pre-COVID-19 environment, it was determined that the price index, the KRW/JPY 100 exchange rate, and the coincident indicators variables had a high influence on short-term international air passenger demand, while the variables of KRW/USD, the composite index of lagging indicators, and the composite index of leading indicators had a lower influence.

Figure 3a,b displays the SHAP significance on short-term daily international air passenger traffic after the pandemic (2020–2021) for the same 10 variables that were used for the pre-COVID-19 analysis. The composite index of lagging indicators appears to have the highest significance, followed by KRW/JPY 100, the KOSPI index, KRW/USD, the composite index of leading indicators, KRW/CNY, the KOSDAQ index, KRW/EUR, the composite index of coincident indicators, and the price index. In the post-COVID-19 environment, it was determined that the variables of the KRW/JPY exchange rate, composite index of lagging indicators, and KOSPI index are of high significance, while KRW/EUR, the composite index of coincident indicators, and the price index are of low importance.

Figure 4a,b displays the calculated SHAP significance for daily international air passenger traffic for a total of 11 variables for which the number of confirmed COVID-19 cases was entered for the post-COVID-19 data (2020–2021). The composite index for lagging indicators has the highest significance, followed by KRW/JPY 100, KRW/USD, the KOSPI index, confirmed COVID-19 cases, the composite index of leading indicators, KRW to CNY, the composite index of coincident indicators, the KOSDAQ index, the price index, and KRW/EUR. Contrary to initial predictions, the number of confirmed COVID-19 cases is of moderate significance.

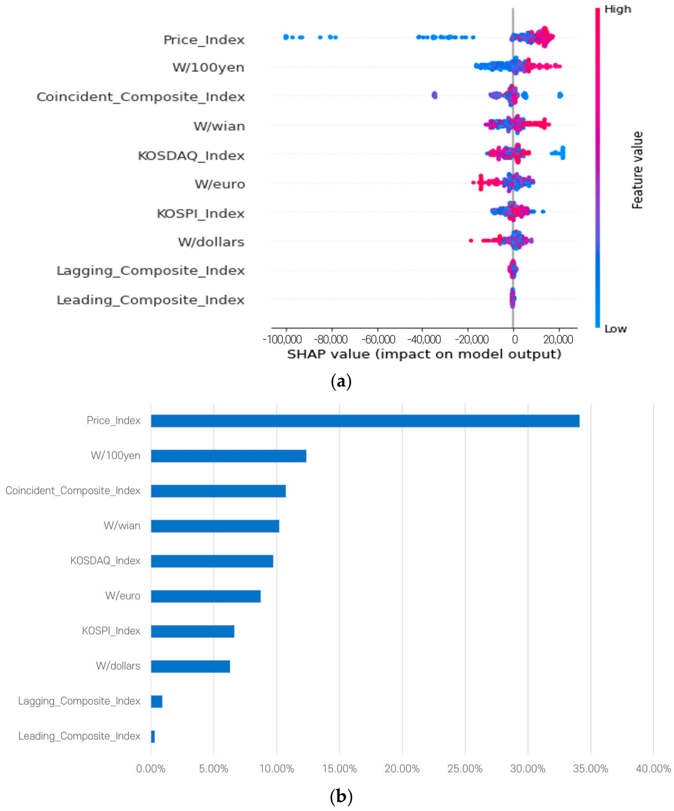

Figure 2. (**a**) SHAP Analysis Results (before COVID-19); (**b**) SHAP Analysis Results (before COVID-19, Absolute Value).

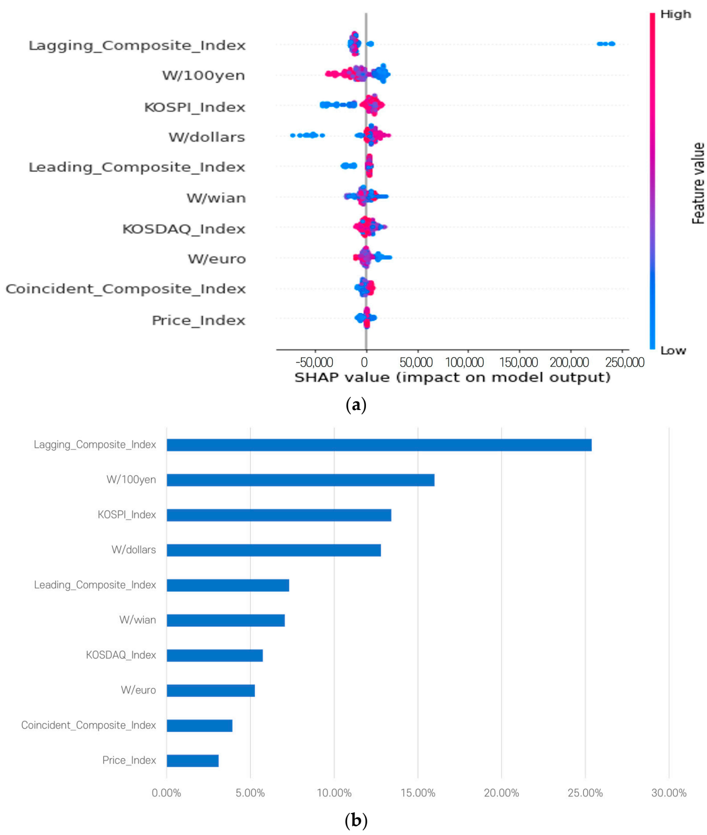

Figure 3. (**a**) SHAP Analysis Results (after COVID-19); (**b**) SHAP Analysis Results (after COVID-19, Absolute Value).

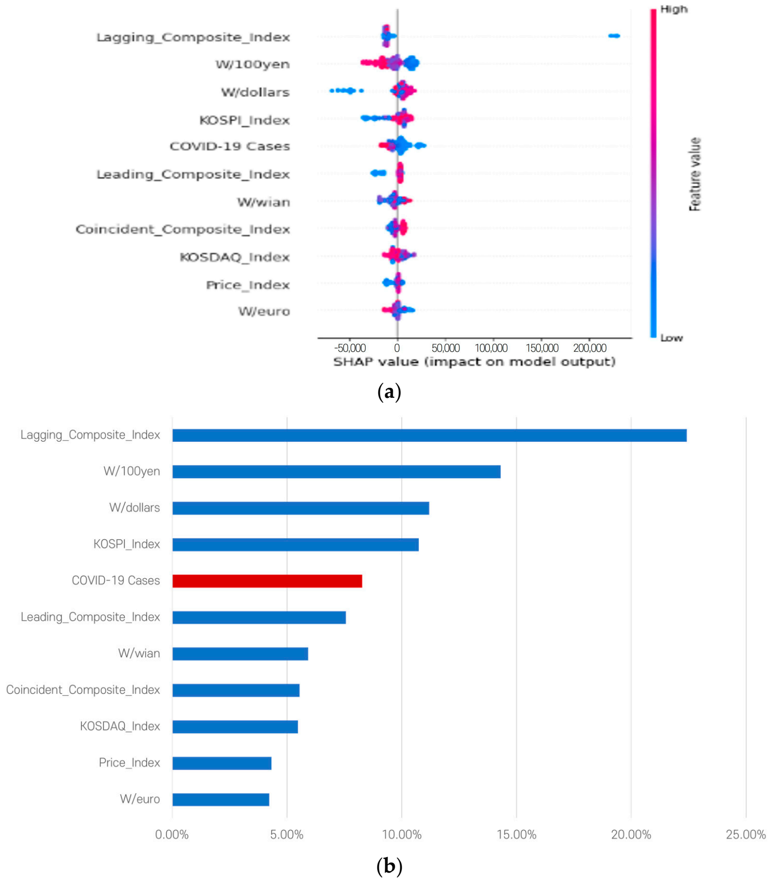

Figure 4. (**a**) SHAP Analysis Results (after COVID-19, Including Pandemic Event Variables); (**b**) SHAP Analysis Results (after COVID-19, Including Pandemic Event Variables, absolute value).

Table 1 shows the significance ranking, percentage, and ranking results from the SHAP analysis before COVID-19. The price index had the highest value, taking up 34.11% of the total SHAP values. In comparison, the composite index of lagging indicators and the composite index of leading indicators accounted for 0.91% and 0.3%, respectively, while the USD exchange rate, which has the lowest value excluding these two indices, was weighted by 6.3%, indicating minimal significance to short-term international air passenger demand, with a large difference from other variables.

Table 1. SHAP Significance and Ranking before COVID-19.

Classification	SHAP Value	Importance Value	Rank
Coincident_Composite_Index	5091	10.72%	3
KOSDAQ_Index	4616	9.72%	5
KOSPI_Index	3149	6.63%	7
Lagging_Composite_Index	432	0.91%	9
Leading_Composite_Index	142	0.30%	10
Price_Index	16,199	34.11%	1
W/JPY100	5868	12.36%	2
W/USD	2991	6.30%	8
W/EUR	4148	8.73%	6
W/CNY	4851	10.22%	4

Table 2 displays the significance ranking, percentage, and ranking results from the SHAP analysis after COVID-19, excluding confirmed cases. The composite index of lagging indicators, which has the highest significance, accounts for 25.73% of the total SHAP values, while the price index has the lowest significance at 3.10%. Although the influence decreases rapidly after the composite index of lagging indicators, it was difficult to conclude that the significance also declines rapidly after that. The significance of the price index, which ranked first before COVID-19, was the least after COVID-19. In contrast, the composite index of lagging indicators was found to have the highest variable significance after COVID-19, despite its extremely low significance before COVID-19.

Table 2. SHAP Significance and Ranking after COVID-19.

Classification	SHAP Value	Importance Value	Rank
Coincident_Composite_Index	3043	3.93%	9
KOSDAQ_Index	4455	5.75%	7
KOSPI_Index	10,396	13.42%	3
Lagging_Composite_Index	19,660	25.37%	1
Leading_Composite_Index	5666	7.31%	5
Price_Index	2402	3.10%	10
W/JPY100	12,394	15.99%	2
W/USD	9918	12.80%	4
W/EUR	4080	5.27%	8
W/CNY	5471	7.06%	6

The results of the post-COVID-19 SHAP analysis with the pandemic variables (event variables) added are shown in Table 3. The composite index of lagging indicators with the highest value accounted for 22.41% of the total SHAP values, whereas the price index and the KRW/EUR exchange rate showed the lowest values with 4.32% and 4.23%, respectively. 8.27% of the total SHAP values was accounted for by the number of confirmed COVID-19 cases. It was determined that there are limitations to asserting that the addition of the variables in the number of confirmed cases significantly changed the overall level of significance.

Table 3. SHAP Significance and Ranking after COVID-19 (Pandemic Variables Included).

Classification	SHAP Value	Importance Value	Rank
Coincident_Composite_Index	4604	5.55%	8
COVID-19 Cases	6857	8.27%	5
KOSDAQ_Index	4539	5.48%	9
KOSPI_Index	8905	10.74%	4
Lagging_Composite_Index	18,577	22.41%	1
Leading_Composite_Index	6276	7.57%	6
Price_Index	3580	4.32%	10
W/JPY100	11,854	14.30%	2

Table 4 provides a comparison of the rate of change in significance before and after COVID-19, excluding the number of confirmed cases. The composite index of lagging indicators, which ranked ninth in terms of highest number among all variables before COVID-19, rose to first place after COVID-19, while the price index fell to tenth from first place. In terms of exchange rates, KRW/EUR and KRW/CNY fell in significance, while

KRW/USD rose and KRW/JPY 100 remained in second place. The level of significance of the variables analyzed in this study for short-term international flights changed before and after COVID-19 (Figure 5).

Table 4. Comparison of Variances before and after COVID-19.

Classification	Importance Value	Rank
Coincident_Composite_Index	−40.24%	▼6
KOSDAQ_Index	−3.50%	▼2
KOSPI_Index	230.19%	▲4
Lagging_Composite_Index	4453.71%	▲8
Leading_Composite_Index	3882.67%	▲5
Price_Index	−85.17%	▼9
W/JPY100	111.20%	-
W/USD	231.62%	▲4
W/EUR	−1.63%	▼2
W/CNY	12.79%	▼2

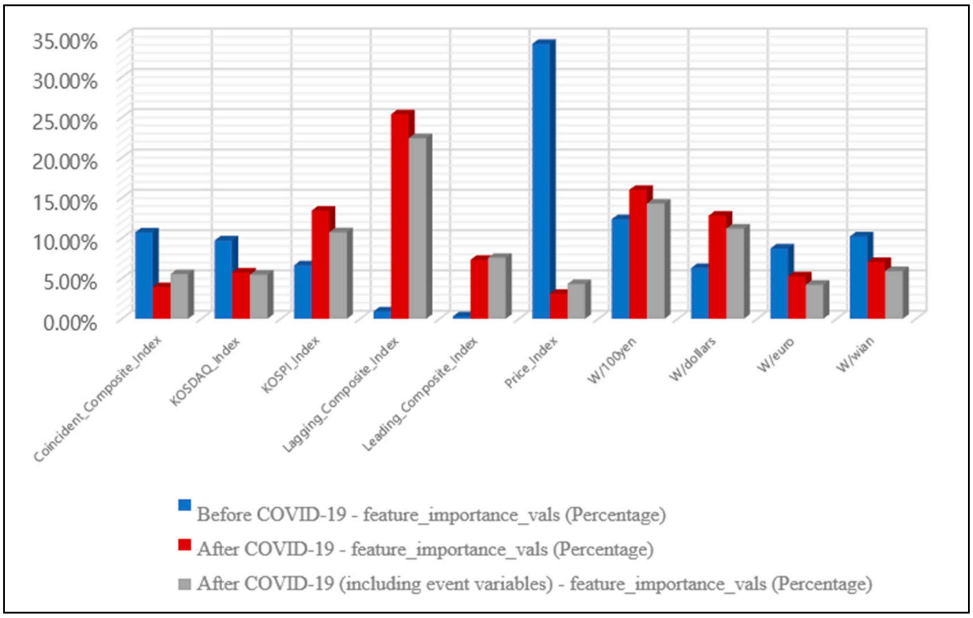

Figure 5. SHAP Analysis—Comparison of Variances before and after COVID-19.

5. Conclusions and Future Research

In order to avoid confirmation bias and hindsight bias, this study examined the factors influencing short-term international air passenger demand using SHAP analysis, an exploratory analysis method. The influence of factors on short-term international air passenger demand, such as before and after COVID-19 and the inclusion of the number of confirmed cases, was taken into account. The hypothesis that there were changes in the number of short-term international air passengers before and after COVID-19 was tested, and it was determined that the number of confirmed cases did not have the greatest direct influence on the short-term demand for international flights.

The most conspicuous finding of this study reveals a shift in the importance of variables. Prior to the pandemic, the price index variable held the utmost significance, whereas the lagging composite index variable exhibited the lowest importance. However, in the post-pandemic period, there was a reversal in the characteristics of these two variables.

Prior to COVID-19, the destination factor, which is similar to economic trends and constitutes international air passenger demand, was analyzed as a significant factor in determining short-term international air passenger demand. Here, it was determined that the price index had the most significant influence on the passenger's decision to use air transportation. It is assumed that consumers choose whether to use air transportation based on price, with the coincident indicator as the third-highest influence. Additionally, it was found that leading and lagging indicators had little influence. Therefore, it can be concluded that the pattern of short-term demand for international flights has a strong correlation with the economic trend. In addition, it was found that the JPY and CNY exchange rates, which account for a large proportion of international air passenger demand in Korea, had an influence on the demand. The USD and EUR exchange rates did not have significant influence and were estimated to be lower than the economic index. It is believed that the short-term influencing factors and their corresponding levels have materialized.

Following COVID-19, it was determined that the short-term demand for international flights did not coincide with economic trends; rather, it was influenced by economic projections. It is believed that this is due to factors such as supply constraints rather than the demand–supply balance on the market in the COVID-19 situation. In fact, unlike before COVID-19, when the lagging indicator was the most influential, the leading indicator had the fifth-largest influence. On the other hand, the coincident indicator and price index were found to have substantially less influence and were more responsive to stable economic trends, such as the KOSPI index, than the KOSDAQ index.

Since a significant portion of short-term international air passenger demand is impacted by lockdown policies in Korea and destination countries, there were significant variances in the exchange rates. First, JPY continued to exert a high level of influence on short-term international air passenger demand, showing a relation to the fact that airline supply is impacted by the international flight policies of Korea and Japan in the wake of COVID-19. On the other hand, CNY's influence diminished because China's lockdown policy made it difficult to meet travel demand. The USD exchange rate was the third most influential factor in short-term international air passenger demand. This is believed to be the case because the purchasing power of the dollar indirectly reflects the unstable market conditions in the COVID-19 situation.

The short-term demand for international flights was affected by the number of confirmed COVID-19 cases, but it appears to have more of a correlation to market conditions than the number of confirmed cases.

Using Korea as an example for this study, it was discovered that short-term international air passenger demand was influenced by economic trends and the proportion of international air passenger demand prior to COVID-19. After the pandemic, however, the short-term demand was influenced by factors including supply constraints and was more sensitive to market conditions resulting from these factors than the number of confirmed cases. This study's findings on the factors influencing short-term international air passenger demand from a macro perspective will contribute to demand forecasting after COVID-19. Furthermore, beginning with this study, we anticipate that exploratory research on countries other than Korea and confirmatory data research based on exploratory research results will be conducted to improve the post-COVID-19 demand forecasting models.

Author Contributions: Conceptualization, K.-H.S.; Methodology, K.-H.S.; Formal analysis, K.-H.S. and S.C.; Investigation, K.-H.S., S.C., S.E. and W.S.; Writing—original draft, K.-H.S. and W.S.; Writing—review & editing, S.E. and W.S. All authors have read and agreed to the published version of the manuscript.

Funding: This study was partly supported by the research grants (NRF-2020R1A2C1011060, and NRF-2022K1A3A1A09078712) funded by the Korean government.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

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