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Using machine learning techniques to assess the financial impact of the COVID-19 pandemic on the global aviation industry

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ABSTRACT

Prediction of financial distress is a crucial concern for decision-makers, especially in industries prone to external shocks, such as the aviation sector. This study employs machine learning techniques on a comprehensive global dataset of aviation companies to develop highly accurate financial distress prediction models. These models empower stakeholders with informed decision-making capabilities to navigate the aviation industry's challenges, most notably exemplified by the COVID-19 pandemic. The aviation industry holds substantial economic importance, contributing significantly to revenue, employment, and economic activity worldwide. However, its susceptibility to external factors underscores the need for robust predictive tools. Leveraging advances in machine learning, this study pioneers the application of data-driven, non-parametric solutions to the aviation sector, both before and after the pandemic. Importantly, this study addresses a gap in the field by conducting comparative evaluations of prediction models, which have been lacking in previous research efforts, often leading to inconclusive outcomes. Key findings of the study highlight the Random Forest and Stochastic Gradient Boosting models as the most accurate in forecasting financial distress within the aviation industry. Notably, the study identifies debt-to-equity, return on invested capital, and debt ratio as the most important predictors of financial distress in this context.

1. Introduction

Accurately forecasting financial distress is of utmost significance for policymakers and investors alike. To make effective policy decisions, it is essential to undertake a careful analysis of the relevant variables whose future values are uncertain, as decisions made by economic and financial entities are significantly impacted by such values. Predicting financial distress enables companies to make necessary adjustments to prevent insolvency and even help in detecting financial crime (Halteh & Tiwari, 2023). The aviation industry is particularly susceptible to financial distress due to its high fixed costs, illiquid assets, and vulnerability to economic downturns. The exploration of the COVID-19 pandemic's impact on the aviation industry is a critical research endeavor. This is because the pandemic has brought about unique and profound disruptions to the industry, necessitating an in-depth investigation to better comprehend its effects.

To address this issue, this study has been conducted that leverages machine learning methods, including Decision Trees (DTs), Random Forests (RFs), and Stochastic Gradient Boosting (SGB) on a global dataset of aviation companies. The objective of this study is to develop Financial Distress Prediction (FDP) models that can accurately forecast financial distress and help investors and policymakers make informed decisions. The models developed in this study can aid in the identification of potential financial distress and enable companies to take necessary actions to avoid such circumstances.

The aviation sector is a critical component of the global economy, as evidenced by its substantial revenue and significant employment and economic activity. In 2020, prior to the COVID-19 pandemic, commercial airlines worldwide generated $872 billion in revenue, which dropped to $382 billion post-pandemic, but has since begun to recover, with revenues increasing to $506 billion in 2021 (**Statistica.com**). The industry employs 29 million individuals and generates $2.9 trillion in economic activity, making it an essential contributor to global economic health (Bisignani, 2024). However, the aviation industry is highly susceptible to external shocks, such as geopolitical and economic uncertainties, as observed in previous studies (Berry, 1992; Bonser, 2019; López Pascual et al., 2021). The COVID-19 pandemic is an example of an unprecedented threat that has severely impacted the aviation industry

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(Arora et al., 2021; Sobieralski and Mumbower, 2022). The pandemic has spread beyond traditional medical boundaries, significantly hindering global businesses, travel, and tourism due to enforced lockdowns and travel restrictions (Kalogiannidis, 2020).

The selection of this research topic is driven by its global significance, as the COVID-19 pandemic has introduced an unparalleled crisis with far-reaching consequences, encompassing the transportation industry in general, including but not limited to the aviation sector (Xuan et al., 2021), shipping freights (Khan et al., 2022; Li et al., 2023), and transportation employment (Mack et al., 2021). Given the aviation industry's pivotal role in global connectivity, trade, and economic advancement, comprehending its financial repercussions during this pandemic assumes utmost importance. Furthermore, the aviation industry's substantial contribution to the global economy, characterized by substantial revenue, employment generation, and economic activity, underscores the profound economic implications of the pandemic's impact, rendering it a compelling and imperative subject for comprehensive research and analysis. The aviation industry has been particularly affected by the pandemic, with a decrease in the number of flights, flight capacity limitations, significant financial losses, and bankruptcies (Xuan et al., 2021). These circumstances further emphasize the importance of conducting an updated assessment of the financial distress in the airline industry. In light of the pandemic's impact on the aviation industry, it is imperative to develop effective tools for predicting and mitigating financial distress to ensure the industry's long-term sustainability.

Recent advancements in machine learning models have greatly improved their effectiveness in the field of forecasting. These models are data-driven and non-parametric, and there are several variants available, including random forests (Breiman, 2001), neural network ensembles (Hansen and Salamon, 1990), and gradient boosting methods (Freund and Schapire, 1997; Friedman et al., 2000; Friedman, 2001).

While previous research has utilized machine learning techniques for FDP, this study is groundbreaking in its application of these methods to the global aviation industry pre- and post-COVID. The innovative use of these advanced techniques aims to provide accurate and reliable predictions of financial distress in the airline industry, thus facilitating effective decision-making for investors and policymakers. The justification for the utilization of machine learning techniques is firmly grounded in their ability to leverage data, thereby improving decision-making processes, automating tasks, and uncovering insights that often remain elusive through traditional methods. In the specific domains of finance, these methodologies play a central role by offering valuable tools for risk mitigation, investment optimization, and adaptation to the dynamic nature inherent in financial markets and economic environments.

There are various stakeholders who could benefit from the findings of this research, including equity holders, managers, financial analysts, auditing firms, creditors, lessors, government agencies, and other interested parties. The development of reliable and accurate models for predicting financial distress is critical for making informed and effective decisions. While many models have been developed for this purpose, comparing the performance of competing prediction models has proven to be a challenging task, often resulting in conflicting results being published.

Few research studied the impact of COVID-19 on the aviation industry, for example, Dube et al. (2021) analysed possible routes towards revival of the global aviation sector, which has been severely affected by the COVID-19 pandemic. Koptseva et al. (2022) developed a model for predicting the bankruptcy of airlines in the Russian Federation. Su et al. (2022) studied the effects of COVID-19 on China's civil aviation passenger transport market. Michelmann et al. (2023) created three potential recovery scenarios for the aviation industry, outlining potential revival paths from COVID-19 until 2030. However, this study pioneers in providing a comprehensive and comparative evaluation of the performance of various machine learning models for predicting financial distress in the global aviation industry pre- and post-COVID. The results of this study will be invaluable for stakeholders who require accurate and reliable models to predict financial distress and make well-informed decisions.

This paper makes a significant contribution by systematically evaluating the financial impact of the COVID-19 pandemic on the global aviation industry through the application of advanced machine learning models, namely decision trees, random forests, and stochastic gradient boosting. Additionally, the research underscores the limited influence of macroeconomic variables and uncertainty measures, emphasizing the prominence of company-specific factors in bolstering airlines' resilience to economic fluctuations. More specifically, this research makes several unique contributions to the existing literature. Firstly, the researchers applied stochastic gradient boosting to predict financial distress in the global aviation industry for the first time. Secondly, the study focuses primarily on the aviation sector, which is a significant contributor to the global economy. Thirdly, it adds to the ongoing discussion about the impact of the COVID-19 pandemic on the global economy. Fourthly, the dataset used covers a significant portion of the global airline industry, enabling the results to be widely applicable. Finally, the study uses distinct macroeconomic variables and uncertainty measures to determine their significance as predictors of financial distress in the aviation industry.

The rest of the paper proceeds as follows: a review of the literature is presented in **Section 2**, whereas **Section 3** describes the data. **Section 4** lays out the methodology. **Section 5** outlines the results. **Section 6** provides a discussion section, while the **Section 7** concludes the study and highlights relevant implications..

2. Literature review

Few studies have evaluated various issues in the prediction of bankruptcy and corporate failure. Beaver (1966) was the first to apply univariate discriminant analysis to selected ratios and found ratios with high predictive power for bankruptcy. Altman (1968) created the first multivariate statistical approach pertaining to FDP – Multiple Discriminant Analysis (MDA). Altman's model was designed to address the main issue faced by Beaver's (1966) model: that different ratios may result in conflicting predictions. Altman formulated a single weighted score (Z) for each business based on five variables. The variables consisted of multiple standard financial and accounting ratios. Altman classified a company as failing if its Z-score was less than 1.8, successful if its Z-score was greater than 2.99, and inconclusive if its Z-score was between 1.8 and 2.99. Altman's model outperformed Beaver's, as the short-term accuracy of the model was 95 %; however, that drops to 72 % when it predicts bankruptcies two or more years in advance.

Altman et al. (1977) provided an improved Z-score by deriving an index called the Zeta model, which was modified in 1993 and was frequently used in the literature as the revised Altman Z-score model. Altman's model was deemed effective for non-manufacturing industries.

The MDA technique was implemented by many researchers to predict air carriers' bankruptcies (Scaggs and Crawford, 1986; Golaszewski and Sanders, 1992; Chung and Szenberg, 1996; Kroeze and Mayer, 2006; Gritta, 1982; and Altman and Gritta, 1984). For example, Gritta (1982) and Altman and Gritta (1984) implemented discriminant analysis specifically in the aviation industry. Applying the Zeta model to the US airline industry, Gritta et al. (2008) indicated the inability of the Zeta model to report the actual coefficients and covariance terms. Dimitras et al. (1996) reviewed 47 studies on business prediction and found that discriminant analysis was the prevailing method of analysis. Although both models are easy to use and have high short-term predictive accuracy, they suffer from some shortcomings. MDA is valid under certain restrictive assumptions of normality and homoscedasticity, which if violated, may result in biased results. In addition, the predictive accuracy of both models declines for long-term predictions.

Many additional contributions were added to the financial distress research in an effort to improve on the predictive power of the original models that utilized MDA. Researchers implemented categorical variable regression models (logit and probit models). For instance, Ohlson (1980) claimed that the output of the MDA model yields a score that lacks intuition and recommended the use of the LOGIT model. Gudmundsson (2002) ran a logistic regression model to predict the probability of airline distress occurring over the years 1996–1998. They included nonfinancial data as proxies for governmental influence and the quality of the economic environment. The researchers found 90 % prediction accuracy. This finding validated their use of non-financial proxies when assessing financial distress. In their research, Chava and Jarrow (2004) suggested estimating the discrete time hazard model with logistic regression. Recently, Alan and Lapre (2018) examined the role played by current operational performance, notably revenue management, operational efficiency, service quality, and operational complexity, in predicting future financial distress in the US airline industry over the period 1988 through 2013. The researchers used logistic regression and found that financial metrics do not fully explain the firm's future financial performance and that operational performance can help predict future financial distress. Although commonly used in the literature to predict bankruptcy, logistics models are sensitive to outliers and expect the observations to be uncorrelated. Furthermore, LM may require more data than MDA to reach reliable results.

To sum up, both MDA and logistic models are simple to apply, are to a certain degree resilient to data that do not fulfill the model's assumptions and have high short-term predictive ability. However, both the DA and logit models suffer from some weaknesses. Linear discriminant analysis does not deal well with nonlinear dependencies. It fails if the discriminant information can be found in the variance but not in the mean. The output of the MDA model produces a score that provides little intuition (Ohlson, 1980). In addition, it does not deal well with highly unbalanced data sets. It is interesting to note that previous studies that implemented MDA, probit, and logit statistical techniques found in general little difference in the predictive accuracy between these models (Hamer, 1983).

Given the shortcomings of MDA and regression models, researchers started using more sophisticated machine learning methods such as the Artificial Neural Network Model (ANN), which is free of the restrictive assumptions required by MDA (Davalos et al., 1999; Gritta et al., 2000). Kumar and Ravi (2007) conducted a *meta*-analysis of 128 artificial intelligence and statistical models for predicting firm and bank failure. They found that the most popular intelligence technique is the neural network model. ANNs are still used in the field of FDP, however, their accuracy is often trumped by boosting methods (Halteh, 2019). A recent study by Halteh and Sharari (2023) used MDA and ANN to quantify the financial distress caused by COVID-19 on Jordanian companies achieving a predictive accuracy of more than 80 %. Although ANN models do not require the pre-specification of a certain functional form and is able to function with imprecise variables, Davalos et al. (1999) noted that the ANN provides results that are inconsistent and can produce different conclusions depending on the place where the algorithm starts in the search area.

MDA, logit, probit, and ANN models were successful in classifying airlines as bankrupt or not based on financial data. However, they are not easy to generalize as they require separable variables that are linear and suffer from a lack of consistency in dealing with a local optimal solution. (Davalos et al. 1999).

Random forests and boosting methods are considered advanced machine learning techniques (Breiman, 2001). The RF technique is an ensemble classification algorithm of weakly correlated or uncorrelated forest decision trees that are built by grouping many trees; thus, they are expected to provide more accurate predictions than each of the individual decision trees. It is referred to as the "ensemble learning method for classification or regression trees." They are created by bagging or bootstrapping samples of the training data and an arbitrary structural selection when the decision tree is initiated. Bootstrapping randomly selects data points from the original dataset to produce a new dataset. The regression output is the mean of every tree generated. RFs are more advantageous than DTs because they effectively handle mixed variables, are easy to use, are invariant to monotonic transformations of input variables, are robust to outliers, and effectively deal with missing data (Chandra et al., 2009).

Another machine learning technique that is a popular learning algorithm is the SGB method. Freund and Schapire (1996) proposed the adaptive boosting technique, which uses the same training data repeatedly. This technique may be utilized in any group learning algorithms. It implements weights that are then used in all training cases (Witten and Eibe, 2005). This technique was followed by a gradient-boosting approach (Freund and Schapire, 1997; Friedman et al., 2000; Friedman, 2001). This technique can achieve a forecast for both classification and regression. Boosting forms a weak model and makes conclusions about the different important parameters and features. Based on these conclusions, a new and more robust model consisting of different trees is generated. In the generation of these trees, the model attempts to minimize the false groupings in the iterations that follow. According to Mueller and Guido (2016), the gradient boosting technique constitutes one of the most powerful and effective machine learning methods. Contrary to conventional boosting methods, the SGB is less affected by data that is contaminated with erroneous target labels and is more accurate than a single model, bagging, or conventional boosting. In addition, SGB is insensitive to erroneous data and requires less data preparation time, imputation of missing values, or pre-processing (Mukkamala et al., 2008).

3. Data

The dataset used in this study was obtained from the widely recognized S&P Capital IQ portal, which offers comprehensive information on companies globally, along with various software applications. This platform is widely used by financial professionals for analyzing company fundamentals, building financial models, and conducting other financial research tasks (Phillips, 2012). In fact, previous studies conducted by Feldman and Zoller (2016), Halteh (2019), Halteh et al. (2018a), and Kahle and Stulz (2013) have relied heavily on Capital IQ for their research.

The initial dataset included 9,387 aviation companies; however, after cleaning the data by excluding companies with any missing information, the final dataset was reduced to 206 companies. Financial and macroeconomic data pertaining to the 206 companies were collected over a four-year period, from 2018 to 2021. The financial data were extracted from end-of-year financial statements for each company, and for the macroeconomic variables, an annual average for each measure was taken.

The dependent variable: the dependent variable used in this study was based on Altman's (1968) Z-Score model; this was done through using Altman's Z-score equation. Z-scores were calculated for each company in the dataset over the four-year period; this enables comparisons to be conducted before, during, and after the pandemic year.

The independent variables: In this study, 23 independent variables were employed as predictors. Careful consideration was given to the selection of these variables, ensuring that financial ratios already accounted for in the Z-Score were not included. This is essential as the dependent variable is based on the Z-Score, and including variables that are already accounted for would likely lead to an overestimation of their importance when analyzing the models. Such a scenario would be misleading since these variables would be directly contributing to the dependent variable.

Company-specific variables: Table 1 showcases 16 variables derived from standard accounting and financial metrics, sourced from the balance sheets and income statements of airline companies. These specific variables were chosen due to their prevalent use in prior empirical research, as well as their availability in existing literature (Halteh 2018;

Table 1
List of independent variables used.

1	Return on Assets (ROA)
2	Return on Capital (ROC)
3	Return on Equity (ROE)
4	Return on Invested Capital (ROIC)
5	Gross Margin
6	Selling, General & Administrative Expenses (SGA)
7	Earnings Before Interest, Taxes, Depreciation, and Amortization Margin (EBITDA Margin)
8	Net Income Margin (NI Margin)
9	Fixed Assets Turnover (FA Turn)
10	Inventory Turnover (Inv Turn)
11	Current Ratio (CR)
12	Quick Ratio (QR)
13	Days Sales Outstanding (DSO)
14	Debt-to-Equity
15	Debt Ratio
16	Debt-to-Earnings
17	S&P Airlines Industry Index (AII)
18	Geopolitical Risk Index (GPR)
19	Global Economic Policy Uncertainty (GEPU)
20	Volatility Index (VIX)
21	Oil Volatility Index (Oil VIX)
22	Daily Infectious Disease Equity Market Volatility Tracker (DIDEMV)
23	Calendar Year

Halteh 2019), and are labeled as variables numbered 1–16 in the table.

Macroeconomics variables: Aiming to get a broader perspective, six mainstream macroeconomic/uncertainty measures were also included as independent variables in this study, namely, the Geopolitical Risk Index (GPR), Global Economic Policy Uncertainty (GEPU), Volatility Index (VIX), Oil Volatility Index (Oil VIX), S&P Airlines Industry Index (AII), and Daily Infectious Disease Equity Market Volatility Tracker (DIDEMV), these are presented as variables numbered 17–22 in Table 1. These variables were chosen to ascertain whether the change in macroeconomic climate – especially due to the COVID-19 pandemic – had any impact on the classification of companies and how important these variables are in determining the financial distress of aviation companies.

The VIX index is the ticker symbol and the popular name for the Chicago Board Options Exchange's (CBOE) Volatility Index, a popular measure of the stock market's expectation of volatility based on S&P 500 index options (Whaley, 2009). Similarly, the CBOE introduced the oil implied volatility (*Oil VIX*) in 2007 as a forward-looking measure of oil volatility. Similar to the VIX index, the calculation relies on call and put options, therefore reflecting market expectations of future volatility. In its part, the *Global Economic Policy Uncertainty* (GEPU) index (Baker et al., 2016), is a GDP-weighted average of national Economic Policy Uncertainty indices (EPU) for 16 countries that account for two-thirds of global output. Finally, Caldara and Iacoviello (2022) construct the *Geopolitical Risk Index* (GPR), a measure of hostile geopolitical events and associated risks based on newspaper news covering geopolitical tensions and their associated economic consequences. These variables were used in previous empirical research (Antonakakis et al., 2013; Kang et al., 2021; McMillan et al., 2021; Ziadat et al., 2022). Following the work of Baker et al. (2019), the newspaper-based *Infectious Disease Equity Market Volatility* Tracker is daily measure available from January 1985 to the present using data from approximately 3,000 US newspapers. *The S&P Airlines Industry Index (AII)* is a generic index that can be used to capture the overall performance of the airline sector; to the best of the authors' knowledge, this variable has never been used before in relation to the application of FDP models to the airline industry.

The last predictor in the analysis is the calendar year, encompassing the years 2018, 2019, 2020, and 2021. The purpose of this variable is to determine the extent to which a particular year, particularly 2020 (the year of the pandemic), may have significantly influenced the classification of companies, as well as to assess the importance of this variable in the determination of the financial status of companies. Variable number 23 in Table 1 represents this predictor. **The complete list of said independent variables are listed in** Table 1**.**

4. Material and methods

The methodology employed in this research is composed of two main components. The first part involves comparing the financial standing of the companies in the dataset for each year between 2018 and 2021, utilising Altman's Z-score. The second part involves developing three distinct machine learning models – DT, RF, and SGB – to determine the most precise model for predicting financial distress among aviation companies and to highlight the most relevant variables with regard to FDP in aviation companies. Both of these components will be elaborated on in separate subsections below.

4.1. Z-score approach

Following the data collection and data cleaning processes, Altman's (1968) Z-Score model was carried out on each company over a four-year period. This will enable comparisons to be conducted before, during, and after the COVID pandemic. This was done using Altman's Z-score equation. The single weighted score (Z) was calculated according to the following formula:

$$Z = 1.2x_1 + 1.4x_2 + 3.3x_3 + 0.6x_4 + 1.0x_5$$

Z: Discriminant score of a company
x_1: Working capital ÷ total assets,
x_2: Retained earnings ÷ total assets,
x_3: Earnings before interest and tax ÷ total assets,
x_4: Market value of equity ÷ book value of total liabilities,
x_5: Sales ÷ total assets.

Following this, a count was carried out for each company in the dataset over the four-year period in order to ascertain the number of companies that are classified as *distressed* ($Z < 1.8$) and *healthy* ($Z > 1.8$). Note that the *inconclusive* category was not used when conducting the analysis, that is, companies that had a Z-Score of $1.8 \leq Z \geq 2.99$ were included in the *healthy* category. This methodology creates a single dichotomous variable and ensures that companies which are truly *distressed* are classified as such.

A comparative analysis was subsequently performed to evaluate whether the Z-scores of the companies were influenced by the pandemic. This was executed by examining the Z-scores of the companies throughout the years and assessing whether the Z-scores of the companies in the dataset have been impacted by the pandemic.

4.2. Machine learning approach

A binary variable was derived from the calculated Z-Scores for each company in the dataset to be used as the dependent variable – it was derived as follows: if the company's Z-Score was less than 1.8, the company was deemed *distressed* and a '1′ was assigned to it; all other companies that did not meet this criterion were deemed *healthy* and assigned a '0′.

The software package, Salford Predictive Modeler, was used for machine learning modelling. The aforementioned software package is a platform that is used for developing both statistical and cutting-edge tree-based models that can deal with complex data – this software has been used previously in the literature, see Gepp and Kumar (2012); Gepp et al. (2010); Halteh (2019); Halteh et al. (2018a, 2018b).

Three machine learning models were created, using DT, RF, and SGB, as follows:

A-The DT model was constructed using the following properties:

- The splitting method for the classification trees was the popular Gini criterion.

- Terminal node must have ≥ 5 companies to avoid overtraining the model, parent nodes ≥ 10 companies in it for the same reason stated earlier.
- Testing method using 10-fold cross-validation

B-The RF model was constructed using the following properties:

- Number of trees built: 500
- Number of predictors: square root number of variables at each node
- Each tree grown to maximum size (as per standard practice)
- Out of bag results for all years for RF
- Balanced errors with 0.47 threshold
- Variable importance - relative according to Gini (standard)

C-The SGB model was constructed using the following properties:

- Number of trees built: 1,000
- Testing method using 10-fold cross-validation
- 0.001 Standard learn rate
- 0.5 Subsample fraction standard
- 6 Max depths of each tree to allow 2–3-way interactions
- balanced rate for evaluation, which has threshold 0.81
- Variable importance - relative according to Gini (standard)

5. Results

5.1. Z-score approach

The findings of this research reveal that in 2018, roughly 67 % of companies were categorized as distressed, while the remaining 33 % were considered healthy. In 2019, approximately 76 % of companies were identified as distressed - a relative percentage increase of around 14 % in distressed companies compared to the previous year. In contrast, the percentage of healthy companies dropped by about 28 %, with only 24 % being classified as healthy. In 2020, around 85 % of companies were deemed distressed - a relative percentage increase of over 12 % compared to the preceding year. As for healthy companies, only 15 % were identified as healthy, resulting in a relative percentage decline of approximately 38 % compared to the previous year. In 2021, roughly 88 % of companies were classified as distressed - a rise of about 3 % in distressed companies compared to the preceding year. In contrast, the percentage of healthy companies dropped by approximately 19 %, with only 12 % being identified as healthy.

The results of the companies classified as distressed or healthy for the years 2018–2021 are displayed in Table 2. The numbers in the table represent the actual count of companies, followed by the percentage they represent in the overall dataset, presented in parentheses. As shown in the table, there is a growing number of distressed companies from year to year and a declining number of healthy companies from year to year.

Table 3 illustrates the percentage year-to-year increase and decrease in distressed and healthy companies, respectively. As indicated in the table, there was a 14 % increase in distressed companies and a drop of about 28 % in healthy companies from 2018 to 2019. From 2019-2020, there was a 12 % increase in distressed companies and a drop of roughly 38 % in healthy companies. Furthermore, from 2020 to 2021, there was a 3 % increase in distressed companies and a drop of approximately 19 % in healthy companies.

Table 2
Company Analysis according to the Z-Score.

	2018	2019	2020	2021
Z < 1.8 (Distressed)	137 (67 %)	156 (76 %)	175 (67 %)	181 (88 %)
Z > 1.8 (Healthy)	69 (33 %)	50 (24 %)	31 (33 %)	25 (12 %)
Total	206 (100 %)	206 (100 %)	206 (100 %)	84 (100 %)

Table 3
Z-Score relative percentage differences for companies between 2019 and 2020.

	2018–2019	2019–2020	2020–2021
% Increase in Distressed Companies	14 %	12 %	3 %
% Decrease in Healthy Companies	28 %	38 %	19 %

The significance of these findings lies in the fact that they reveal a concerning trend leading up to the pandemic year, with an uptick in the number of financially distressed companies and a decline in the number of healthy ones. The situation worsened considerably during the pandemic year of 2020, with an unprecedented drop of approximately 38 % in the number of healthy companies, alongside a significant increase of around 12 % in the number of distressed companies. The economic turmoil of the pandemic, characterized by widespread shutdowns and changes in consumer behavior, left many businesses struggling to survive, with even some of the most stable companies facing significant challenges.

The good news is that there are signs of a recovery in the post-COVID era, with the number of distressed companies starting to fall sharply in 2021. However, it is worth noting that the number of healthy companies has not yet fully rebounded, and the rate of decline in 2021 was still higher than in previous years, indicating that the effects of the pandemic continue to be felt across industries. Despite this, the fact that the rate of decline in healthy companies was the lowest in comparison to the previous years is an encouraging sign that the situation is gradually improving.

Overall, these findings underscore the need for continued support and innovative solutions to help businesses navigate the challenges of the current economic climate and build resilience in the face of future uncertainties.

5.2. Machine learning approach

5.2.1. Decision tree model

Table 4 shows the testing phase confusion matrix for the DT model. As is evident, the model was able to correctly classify 79.43 % (specificity) of *healthy* companies and 79.97 % (sensitivity) of *distressed* companies. These results yielded an overall correct prediction percentage of 79.85 % and a precision of 93.51 %.

Table 5 shows the Area Under the Receiver Operating Characteristic (AUROC) score, which is a performance measure for the ROC, i.e., the closer the area is to 1, the more accurate the model (Halteh, 2019). In the learning phase, the AUROC score was 90.28 %, but it dropped to 82.78 % in the testing phase. This is common with decision trees since they are more volatile to changes in data, which is why more complex tree-based models, such as RF and SGB tend to be more reliable.

Table 6 shows the normalised variable importance for the DT model. As is shown, the top five predictive variables chosen by the model are:

Table 4
Confusion Matrix – Testing.

ActualClass	Total Class	Percent Correct	Predicted Classes	
			0 N = 269	1 N = 555
0	175	79.43 %	139	36
1	649	79.97 %	130	519
Total:	824			
Average:		79.70 %		
Overall % Correct:		79.85 %		
Specificity		79.43 %		
Sensitivity/Recall		79.97 %		
Precision		93.51 %		
F1 statistic		86.21 %		

Table 5
Area Under the Receiver Operating Characteristic Curve.

Name	Learn	Test
ROC (Area Under Curve)	0.90277	0.82777

Table 6
Normalised Variable Importance.

Variable	Score
TL_TA	100.00
TD_TE	87.23
CR	77.63
ROIC	74.25
ROC	70.61
TD_EBITDA	61.04
ROE	57.77
FA_TURN	51.77
NI_MARGIN	51.19
ROA	49.93
QR	40.81
EBITDA_MARGIN	35.39
GROSS_MARGIN	33.61
YEAR	15.22
VIX	14.59
OIL_VIX	14.46
GPR	14.46
DIDEMV	14.46
SGA	11.87
DSO	8.66
INV_TURN	8.51
GEPU	3.97

1. Debt Ratio
2. Debt-to-Equity
3. Current Ratio
4. Return on Invested Capital
5. Return on Capital

5.2.2. Random forests model

Fig. 1 shows the balanced error rate versus the number of trees built for the RF model. As is evident from the chart, after around 50 trees, there is no significant improvement in terms of error reduction. Therefore, building 500 trees was more than sufficient to achieve an optimal model using RFs.

Table 7 shows the testing phase confusion matrix for the RF model. As is illustrated, the model was able to correctly classify 84 % (specificity) of healthy companies and 84.28 % (sensitivity) of distressed companies. These results yielded an overall correct prediction percentage of 84.22 % and a precision of 95.13 %. Consistent with previous literature such as Halteh (2018); Halteh (2019), the RF results are more accurate than those of the DT model.

Table 8 shows the AUROC score. The Out of Bag (OOB) score was 93.62 %. Again, this is significantly better than the DT model.

Table 7
Confusion Matrix – Testing.

ActualClass	Total Class	Percent Correct	Predicted Classes	
			0 N = 249	1 N = 575
0	175	84.00 %	147	28
1	649	84.28 %	102	547
Total:	824			
Average:		84.14 %		
Overall % Correct:		84.22 %		
Specificity		84.00 %		
Sensitivity/Recall		84.28 %		
Precision		95.13 %		
F1 statistic		89.38 %		

Table 8
Area Under the Receiver Operating Characteristic Curve.

Name	OOB
ROC (Area Under Curve)	0.93617

Table 9 shows the normalised variable importance for the RF model. As is shown, the top five predictive variables chosen by the model are:

Return on Invested Capital
Debt-to-Equity

Table 9
Normalised Variable Importance.

Variable	Score
ROIC	100.00
TD_TE	99.62
ROE	99.10
TL_TA	94.68
CR	89.52
TD_EBITDA	73.06
ROC	67.65
NI_MARGIN	56.67
FA_TURN	41.22
ROA	34.37
QR	32.74
GROSS_MARGIN	16.39
EBITDA_MARGIN	13.99
DSO	9.06
INV_TURN	7.47
SGA	5.57
YEAR	4.19
GPR	1.69
VIX	1.33
OIL_VIX	0.60
DIDEMV	0.50
GEPU	0.32

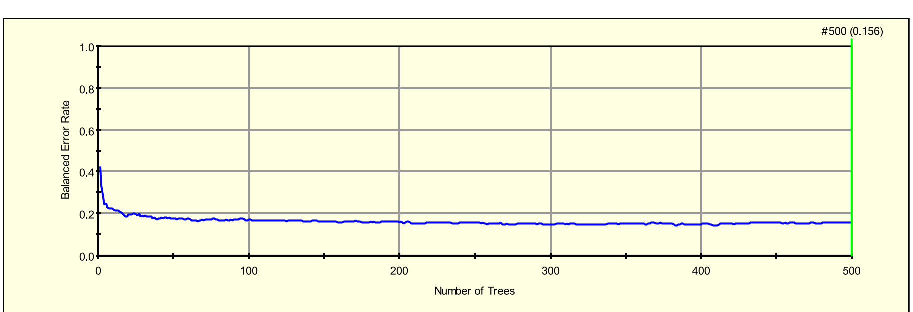

Fig. 1. Balanced Error Rate vs Number of Trees Built for the RF Model.

Return on Equity
Debt Ratio
Current Ratio
Stochastic Gradient Boosting Model

Fig. 2 depicts the average error rate versus the number of trees constructed using SGB. The chart shows that there was a decrease in the error rate of the model achieved through constructing more trees. Therefore, building 1000 trees was justified, as the error rate began to plateau towards the end, indicating no or very little added value to be gained by building more trees.

Table 10 shows the testing phase confusion matrix for the SGB model. As is evident, the model was able to correctly classify 84.57 % (specificity) of healthy companies and 83.36 % (sensitivity) of distressed companies. These results yielded an overall correct prediction percentage of 83.62 % and a precision of 95.25 %.

Table 11 shows the AUROC score. In the learning phase, the AUROC score was 96.07 %, but it dropped to 92.03 % in the testing phase. This is a minor drop compared to the DT model, as is expected from the more accurate SGB model.

Table 12 shows the normalised variable importance for the SGB model. As is shown, the top five predictive variables chosen by the model are:

1. Debt Ratio
2. Return on Invested Capital
3. Return on Capital
4. Fixed Assets Turnover
5. Debt-to-Equity

The findings derived from the analysis of the three machine learning models highlight the significant role of debt-to-equity, debt ratio, and return on invested capital across all models. These variables are consistent with prior research on the prediction of financial distress among companies in other industries, as documented in studies such as Halteh (2019) and Halteh et al. (2018). Nonetheless, this research is the first to demonstrate empirically the importance of these variables when applied to companies operating in the aviation industry.

Another important finding is that the calendar year variable, as well as all of the macroeconomic/uncertainty measures used in this study were deemed of very little importance across all machine learning models. This demonstrates that the ratios which were found to be of high importance in this study and in previous literature, are impervious to extraneous factors, be it a pandemic or otherwise.

6. Discussion

During 2020, government support for the aviation industry has taken various forms, such as stimulus packages, capital injections, loans, tax deferral, and tax reduction (Xuan et al., 2021). Notably, the US government provided $25 billion in payroll support to U.S. airlines through the Coronavirus Aid, Relief, and Economic Security (CARES) Act, while in the European Union, a €7 billion aid package was proposed by the European Commission, comprising loans and guarantees for airlines. Additionally, the UK government provided £600 million in loans and grants to support the aviation industry. The primary objective of these government initiatives was to provide temporary relief to airlines until the air travel demand recovered, despite the fact that they were distributed unequally across different regions. Although the impact of government aid is undoubtedly significant, this study did not account for the impact of government aid distributed during the COVID-19 pandemic in 2020, as such information was unavailable for all airlines.

Table 10
Confusion Matrix – Testing.

ActualClass	Total Class	Percent Correct	Predicted Classes	
			0 N = 256	1 N = 568
0	175	84.57 %	148	27
1	649	83.36 %	108	541
Total:	824			
Average:		83.97 %		
Overall % Correct:		83.62 %		
Specificity		84.57 %		
Sensitivity/Recall		83.36 %		
Precision		95.25 %		
F1 statistic		88.91 %		

Table 11
Area Under the Receiver Operating Characteristic Curve.

Name	Learn	Test	Learn Sampled
ROC (Area Under Curve)	0.96073	0.92026	0.95825

Table 12
Normalised Variable Importance.

Variable	Score
TL_TA	100.00
ROIC	80.51
ROC	80.29
FA_TURN	62.39
TD_TE	60.15
CR	51.04
TD_EBITDA	34.52
ROA	32.02
DSO	24.36
INV_TURN	24.16
ROE	23.83
QR	22.47
GROSS_MARGIN	21.26
EBITDA_MARGIN	20.99
SGA	19.38
NI_MARGIN	17.48
YEAR	10.78
DIDEMV	3.44

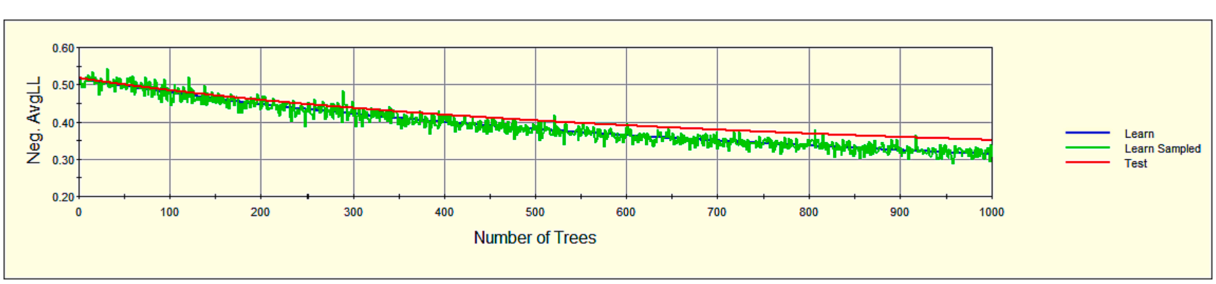

Fig. 2. Average Error Rate vs Number of Trees Built for the SGB Model.

Based on the findings generated by the Altman Z-score model, the number of companies classified under the category of financial distress appeared to increase in 2020, which could potentially be linked to the COVID-19 pandemic. However, the study discovered that the predictors used to forecast firms' financial distress remained consistent before, during, and after the pandemic year, implying that they were not affected by any external or macroeconomic factors. This observation highlights the robustness of the FDP model and indicates that the selected variables were resilient to the unprecedented economic turbulence resulting from the pandemic. The study's results suggest that the FDP model could continue to be an effective tool for companies and investors to identify the early warning signs of financial distress, even in periods of significant macroeconomic uncertainty. Nonetheless, it is worth noting that the ongoing impact of the pandemic and the availability of government aid may have influenced the financial health of companies, which the FDP model may not have fully captured in its analysis.

The airline business is observed to have a low profit margin, even when the economic conditions are favourable. As a result, only a limited number of industry players can generate enough profits during times of economic growth to accumulate adequate reserves for the downturns. This low-profit margin phenomenon is a critical reason why state-owned airlines receive significant subsidies, and also why the US government had to provide financial assistance in the form of guaranteed loans to major US airlines during the airline industry's severe downturn in September 2001. Such financial support implies that it is challenging to defend the global aviation industry as a free and open market, as governments worldwide may need to intervene constantly in the industry. (Doganis, 2006).

Furthermore, fuel costs are a major expense for airlines, typically accounting for 30 % to 50 % of their operating expenditures. Sudden and disruptive fluctuations in fuel prices can have a significant impact on an airline's financial health. In response, most airlines have entered into long-term supply contracts with oil companies that have clauses for price adjustments according to global market price fluctuations. Additionally, risk exposure can be mitigated through derivative instruments including forwards, futures, options, swaps, and collars (Morrell, 2009).

Jet fuel prices are a critical exogenous factor in the airline sector since they constitute a significant part of an airline's operational costs and are highly sensitive to price fluctuations. As a result, most airlines adopt fuel-hedging tactics to reduce the risk of price fluctuations. A vast majority of studies reveal that fuel price hedging is a favorable risk management tool that has a positive impact on business value. Specifically, studies conducted by Korkeamaki et al. (2016) and Alnuaimi (2015) have shown favorable associations between fuel price hedging and business value.

7. Conclusions

The aim of this research was to evaluate the financial impact of the COVID-19 pandemic on the global aviation industry. To achieve this, the study developed and tested three different machine learning models, namely DT, RF, and SGB models. These models were utilized to predict the financial distress of companies within the aviation industry. Based on the analysis conducted, the main results of the study suggest that the RF and SGB models are the most accurate in predicting financial distress in the aviation industry. This is due to the fact that these models utilize multiple decision trees for classification purposes, which allows for more accurate and robust predictions. The results highlighted debt-to-equity, return on invested capital, and debt ratio as the most important predictors of financial distress.

Comparing Z-scores of companies before, during, and post COVID-19, it was evident that companies in the aviation industry increased in financial distress during the pandemic, however, they started to recover in 2021. Interestingly, the calendar year variable, as well as all of the macroeconomic/uncertainty measures used in this study were deemed of very little importance across all machine learning models.

While macroeconomic conditions can exert an influence on the aviation sector and individual airlines, they do not represent the primary driver of aviation stress and bankruptcy predictions. Rather, a combination of company-specific factors, such as diverse income streams, fuel hedging techniques, and a strong financial position, can significantly bolster an airline's resilience to macroeconomic fluctuations and decrease the probability of experiencing financial distress and insolvency.

The research study, while significant, did not factor in the potential impact of government aid during the COVID-19 pandemic in 2020 as complete information was not readily available for all airlines. It is worth noting that during this period, governments worldwide provided various forms of support, including capital injections, loans, tax deferrals, and reductions. The primary aim of such aid was to provide airlines with temporary relief to manage the economic fallout from the pandemic, with the expectation of a recovery in air travel demand. However, it is important to recognize that the distribution of this aid varied across regions and among individual airlines.

In the airline industry, bankruptcy prediction models can be particularly important given the high levels of capital investment required to operate and the inherent volatility of the industry. Airlines are often subject to numerous external factors that can impact their profitability, such as fuel prices, government regulations, competition, and economic downturns.

By applying bankruptcy prediction models, airlines can identify potential financial issues early and take corrective actions to prevent insolvency. For example, airlines can use these models to monitor key financial metrics such as liquidity, profitability, and debt levels, and take action to improve their financial position before it becomes too late. Additionally, the use of bankruptcy prediction models can help airlines secure funding and investments from lenders and investors, as they can provide a more accurate assessment of the company's financial health.

Furthermore, by identifying key predictors, the study provides valuable insights for investors, policymakers, and industry stakeholders who are interested in understanding the financial health of the aviation industry in the context of the COVID-19 pandemic. The findings can be used to inform decision-making processes that aim to mitigate the impact of the pandemic on the industry, and to support long-term sustainability of the industry.

This research recommends that airline companies concentrate on their debt-to-equity, return on invested capital, and debt ratios as the most important factors because they are the best predictors of financial distress. To add, the research offers a set of practical policy recommendations; these recommendations encompass the implementation of machine learning-driven early warning systems for continuous monitoring of financial distress indicators. In addition, it provides dynamic risk assessment to enable proactive risk management, tailored financial support measures based on machine learning insights and adaptive regulatory frameworks. It helps in enhancing the supply chain resilience and optimized resource allocation and the integration of machine learning insights into long-term sustainability planning. These recommendations emphasize the importance of data-driven, proactive strategies for crisis management and sustainable development within the aviation sector, highlighting the pivotal role of machine learning in informed policymaking.

Moreover, the research carries substantial policy relevance, addressing the imperative need for data-driven insights among policymakers, industry stakeholders, and investors. Informed policy formulation, resource allocation, and decision-making are contingent upon comprehensive data analysis facilitated by machine learning, offering practical and actionable recommendations. Overall, this study highlights the importance of financial distress prediction and emphasizes the need for accurate and reliable forecasting methods, particularly in vulnerable industries such as aviation.

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CRediT authorship contribution statement

Khaled Halteh: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation. **Ritab AlKhoury:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Investigation. **Salem Adel Ziadat:** Writing – review & editing, Writing – original draft, Visualization, Validation. **Adrian Gepp:** Supervision, Software, Resources, Project administration, Methodology, Data curation. **Kuldeep Kumar:** Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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