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Estimating the impact of COVID-19 on air travel in the medium and long term using neural network and Monte Carlo simulation

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ABSTRACT
The COVID-19 pandemic has had a substantial impact on the airline industry. Air travel in the United States declined in 2020 with significantly lower domestic and international flights. The dynamic change and uncertainty in the trend of COVID-19 have made it difficult to predict future air travel. This paper aims at developing and testing neural network models that predict domestic and international air travel in the medium and long term based on residents’ daily trips by distance, economic condition, COVID-19 severity, and travel restrictions. Data in the United States from various sources were used to train and validate the neural network models, and Monte Carlo simulations were constructed to predict air travel under uncertainty of the pandemic and economic growth. The results show that weekly economic index (WEI) is the most important predictor for air travel. Additionally, daily trips by distance play a more important role in the prediction of domestic air travel than the international one, while travel restrictions seem to have an impact on both. Sensitivity analysis results for four different scenarios indicate that air travel in the future is more sensitive to the change in WEI than the changes in COVID-19 variables. Additionally, even in the best-case scenario, when the pandemic is over and the economy is back to normal, it still takes several years for air travel to return to normal, as before the pandemic. The findings have significant contributions to the literature in COVID-19’s impact on air transportation and air travel prediction.

1. Introduction

The COVID-19 pandemic has significantly affected the airline industry. In order to reduce the spread of coronavirus, many countries have issued travel restrictions, especially air travel, to limit the travel volume. In the United States, many states limit air travel by mandating self-quarantine for people arriving from other states or countries by air. This requirement has affected many business and personal trips as it causes disruption in business operations or personal activities. Many organizations have moved to working from home and using Zoom meetings to avoid any interruption. People chose to travel by car whenever possible. As a result, air travel has reduced significantly. Figs. 1 and 2 show the comparison of commercial flights between 2019 and 2020. It appears that the number of commercial flights, both domestic and international, has declined significantly amid the pandemic. Before the pandemic, there was an average of 25,000 domestic flights and 4300 international flights per day in 2019. Since early April 2020, when most states issued stay-home orders, the number of flights reduced significantly to less than 10,000 domestic flights and about 500 international flights per day. While these numbers started to rise again in early July 2020, they are still far below the number of flights in the same month in 2019. From July to December 2020, the number of daily domestic flights was about 15,000, whereas daily international flights ranged from 1000 to 1500 (BTS, 2020a).

In this study, air travel is measured by the number of domestic and international flights. While flights during the pandemic may not be full, this number is not too far off the actual travel demand. Fig. 3 shows the actual number of people checked in daily at U.S. airports for both domestic and international flights. We can note the similar trends of these numbers compared to the trends of domestic and international flights. There was a sharp fall in April 2020, followed by a slow gain from June to August 2020. Then, the demand gradually increased toward the end of December 2020. Thus, the number of flights does capture well the patterns of travel demand by U.S. residents. One advantage of using the number of flights is that it allows airlines to easily estimate their revenues and expenses in the future, which helps determine the timeline for the airline industry recovery.

The decreased air travel has had negative impacts on the airline
The literature on COVID-19 predict air travel during and post COVID-19 is still missing. and how airlines reacted to travel restrictions. A specific model that can limited and focused primarily on the impact differences between regions and transport behavior is dynamic and unpredictable with a high uncertainty level. Thus, a good prediction needs a capability to capture the including the September 11 event. The impact of COVID-19 on society and the airline industry has never experienced anything like this before, mining air travel demand, they do not reflect how the demand changes amid a pandemic, especially an unprecedented one like COVID-19. The answers to these questions can provide useful information about the status of the airline industry in the medium and long term. The traditional literature in air travel prediction tends to focus on macro factors, such as population demographics, location, economic, consumption expenditure, and deregulation, and micro factors, including airlines’ service, pricing, and quality (Wang and Song, 2010; Valdes, 2015). While these factors still play an important role in determining air travel demand, they do not reflect how the demand changes amid a pandemic, especially an unprecedented one like COVID-19. The airline industry has never experienced anything like this before, including the September 11 event. The impact of COVID-19 on society and transport behavior is dynamic and unpredictable with a high uncertainty level. Thus, a good prediction needs a capability to capture the dynamism of the pandemic and the change in people’s travel behavior. The literature on COVID-19’s impact on air transportation is rather limited and focused primarily on the impact differences between regions and how airlines reacted to travel restrictions. A specific model that can predict air travel during and post COVID-19 is still missing.

The purpose of this paper is to predict air travel in the U.S. during and post COVID-19 using novel variables. These novel variables are U.S. residents’ daily trips by distance since their daily travel decisions change dynamically according to their risk perception of COVID-19. Research shows that the more trips people make amid the pandemic, the safer they feel in their travels (Beck and Hensher, 2020). In addition, the trip distance does play an important role in their travel behavior in responding to changes in COVID-19 cases and deaths. More specifically, the residents tend to make short trips right after they notice the decrease in COVID-19 cases and deaths, while it takes them more time to decide to make medium and long trips (Truong and Truong, 2021). Thus, it is possible that residents’ daily travel behavior can capture the dynamism of the transport pattern during and post pandemic. Finding whether these novel variables can predict air travel is the purpose of this study. Other input variables include the economic index, COVID-19 variables, and travel restrictions in order to capture the spread and severity of the pandemic and the economic condition. Neural network and Monte Carlo simulation are appropriate methods to find a pattern of relationship between input variables and air travel and to perform what-if-scenarios to predict the air travel volume during and post COVID-19. This paper’s findings add value to the air transportation literature by examining the effects of novel variables, daily trips by distance, and modeling the air travel under uncertainty. The sensitivity analysis results provide a prediction of air travel in various scenarios, which can help the government and airlines make informed decisions to formulate policies and strategies to survive this crisis. It is important to note that this paper does not aim at performing time series forecast, as this method assumes temporal dependency of the air travel. Given the rapidly changing situation of COVID-19 and unclear patterns in the past, time series forecast models may need to be updated frequently to be meaningful (Truong and Truong, 2021). Accordingly, the simulation results in this paper can provide more useful information to run several what-if scenarios to examine how air travel will be during and post pandemic.

The paper is organized as follows. Section 2 reviews the existing literature in air travel prediction and COVID-19’s impacts on air transportation. Research gaps are discussed, along with the explanation for the contributions of this study. Section 3 describes the data sources, variables, and research methodologies, including neural network and Monte Carlo simulation. Section 4 provides detailed results of the neural network models, simulation results, and sensitivity analysis results. Finally, Sections 5 and 6 discuss the research findings, implications of the study, and recommendations for future research.

![Fig. 1. U.S. domestic commercial flights in 2019 and 2020 (BTS, 2020a).](image)
2. Literature review

2.1. Previous works

There has been a large number of studies on air travel demand in the literature. Wang and Song (2010) did a comprehensive review of the literature on air travel demand, showing a large number of studies in this direction. Predictors for air travel demand have typically been categorized into those outside and those inside the scope of airline control (Valdes, 2015). Macro factors that are not in the control of airlines include economic, cultural, locational, and political characteristics of the population in a specific country. Some specific variables are population demographics (Abed et al., 2001; Bafail et al., 2000; Jorge-Calderon, 1997; Sivrikaya and Tunç, 2013; Castelli et al., 2003), gross domestic product (GDP) or GDP per capita (Cheze et al., 2012; Gillen, 2013; Kincaid and Tretheway, 2013; Vedantham and Oppenheimer, 1998; Cline et al., 1998; Valdes, 2015), total consumption expenditure (Abed et al., 2001; Bafail et al., 2000), distance (Gillen, 2013; Grosche et al., 2007; Sivrikaya and Tunç, 2013), and deregulation (Adler and Hashai, 2005; Gillen, 2013; Kincaid and Tretheway, 2013; Fu et al., 2009). In addition, micro factors capture pricing, service, and quality provided by airlines (Oum et al., 1992; Jorge-Calderón, 1997; Sivrikaya and Tunç, 2013; Chin, 2002; Castelli et al., 2003; Mason, 2005; Graham, 2006; Bieger et al., 2007; Ortúzar and Simonetti, 2008). These factors are in the control of airlines and determined by airline’s operational and marketing strategies.

While these studies have significant contributions to the air transportation literature, their findings do not directly apply to the current crisis due to COVID-19 in 2020. The pandemic is an unprecedented situation with many new, unpredictable variables that have not been experienced before. In addition, the COVID-19 trend dynamically changes every day with unknown patterns, which makes it difficult to predict the trend of the pandemic and its impacts on our economy. The macro and micro factors mentioned above need to be measured over a long period of time to provide meaningful results. Their effects on air travel during and post COVID-19 are also unknown; hence, they cannot be used as reliable predictors for the purpose of this study.

Since the beginning of COVID-19 in late January 2020, numerous studies have been conducted on how COVID-19 has impacted the transportation industry and residents’ travel safety. Loske (2020) studied the impact of COVID-19 on transportation volume and freight capacity dynamic and found that the increasing freight volume did not depend on the duration of the COVID-19 epidemic but the total number of new infections per day. Katrakazas et al. (2020) investigated the effect of COVID-19 on driving behavior and road safety in Greece and Saudi Arabia and found that COVID-19 led to increased speeds, harsh events, and use of the mobile phone during driving. Abdullah et al. (2020) indicated residents’ trip purpose, mode choice, travel distance, and trip frequency were significantly different before and during the pandemic. Gender, car ownership, employment status, travel distance, traveling purpose, and pandemic-related underlying factors were found to be important predictors of mode choice during the pandemic. A study by Karaer et al. (2020) showed that COVID-19 reduced vehicle travels in all Florida counties, which resulted in a significant reduction in traffic.

There are two interesting studies focused on travel behavior. Beck and Hensher (2020) found that while travel risk perception increased with age, it decreased with travel frequency, i.e., the more trips someone makes, the lower the risk perception of the virus infection. Truong and Truong (2021) also focused on residents’ travel behavior by investigating a dynamic relationship between daily travel behavior and COVID-19 infection. The authors found that people reacted and changed their travel behavior more quickly for short trips than long trips. There was a time lag between the change of COVID-19 infection and the change of people’s long-distance travel behavior. In other words, when people start making more short trips, they may feel safer and later decide to travel a longer distance. This finding is essential to understand how people make decisions in choosing the distance for travel.

The number of studies on COVID-19’s impacts on air transportation is rather limited and lacks focus. Gudmundsson et al. (2021) developed a time series forecast model to estimate the recovery time for the airline industry, both passenger carriers and air freight, by regions in the world. The authors found that it might take 2.4 years for the passenger carriers to come back to normal. The Asia Pacific has the shortest average recovery time, followed by North America and Europe. Monmoussear et al. (2020) analyzed the effect of travel restriction measures during COVID-19 from a passenger perspective in the U.S. air transportation system. The authors found that airlines had reacted differently to the COVID-19 travel restriction measures and proposed specific metrics to improve airlines’ decision making process. Maneenop and Kotcharin (2020) examined the short-term impacts of COVID-19 on 52 airlines worldwide and found that traders in Western countries were more responsive to recent information than the rest of the world. The results also showed that airline stock returns declined faster than the market returns after three major COVID-19 announcements. Sun et al. (2020) investigated COVID-19 impact on air transportation by comparing the service data from 150 airlines between 2751 airports. They found that the impact of the COVID-19 pandemic on international flights was much stronger than on domestic flights. Additionally, Bauer et al. (2020)

\[\text{Fig. 2. U.S. international commercial flights in 2019 and 2020 (BTS, 2020a).}\]
investigated the impact of COVID-19 on ultra-long-haul (ULH) operations worldwide. The scenario analysis results indicated that point-to-point ULH services would require minimal adjustments to cope with COVID-19. The operations should be able to simultaneously produce higher seat-load factors and increased network flexibility to bypass hub airports with dense populations. Last but not least, Forsyth et al. (2020) analyzed airports’ price changes in responding to demand collapse prompted by COVID-19. Airports would adjust their price charges in different ways to a large demand decline. However, if the demand declines due to changes in government policy, airports may need financial assistance.

2.2. Research gaps

While traditional literature in air travel prediction is amply, the determinants, both macro and micro factors, used in those studies do not apply to the current COVID-19 crisis. These factors need to be measured for a certain period of time to be meaningful, and their impacts on air travel only work on the assumption that no unexpected disruption of the socio-economic system occurs. The impacts of COVID-19 on factors such as GDP, population characteristics, locations, regulatory changes, and airlines’ strategic and operational decisions do not show immediately. There is a time lag between observing the spread of COVID-19 and measuring the pandemic’s consequences to the economy and airline industry. In other words, we may need to wait for some time before we can accurately measure changes in those factors caused by COVID-19. With uncertainty and unpredictability in the trend of COVID-19, an alternative method is needed to predict air travel during and after this crisis.

The recent growth of literature on COVID-19 further indicated a need for understanding how COVID-19 had impacted our transportation system and economy. Numerous studies found interesting findings on how residents’ travel behavior and risk perception had changed in responding to the spread of the pandemic. They also highlighted how the transportation system had tried to adapt to a new era given the travel restrictions and declined demand. While studies on COVID-19’s impact on air transportation are somewhat limited, they did show differences among countries and airlines in responding to COVID-19. However, most of those studies used aggregate data, which did not capture the dynamism and uncertainty of the COVID-19’s trend. Additionally, none of them have taken into account the uncertainty of the economic conditions, COVID-19 severity, and residents’ travel behavior in estimating air travel. Furthermore, there is a lack of a model that estimates domestic and international flights during and post COVID-19 based on different scenarios. While the decrease in air travel due to COVID-19 in 2020 was very apparent, it is important to predict and evaluate how air travel volumes will change in different scenarios of the economy, COVID-19 severity and progress, and global travel policies. This is a very important question that has not been answered in the extant literature.

2.3. Novel variables

The current COVID-19 crisis is unprecedented, which requires a novel and special way to investigate the impact of COVID-19 on the airline industry in the medium and long terms. This paper aims to fill the research gaps mentioned above by incorporating novel variables in the prediction model. For this purpose, the selection of these variables is not grounded in traditional literature. Two important COVID-19 studies that helped determine these novel variables are the studies by Beck and Hensher (2020) and Truong and Truong (2021). Beck and Hensher (2020) indicated an important finding that residents’ perceived risk was negatively correlated with the number of trips they make. Thus, the more trips someone makes, the lower the risk perception of the virus infection or the safer they feel. In other words, the residents would feel safer and more comfortable traveling more. Truong and Truong (2021) further expanded this direction by analyzing daily travel data by U.S. residents. The authors found that residents’ travel behavior changed dynamically in responding to the change in COVID-19 infection and severity, including new cases and new deaths. A surge in COVID-19 cases and deaths lead to lower daily trips. On the contrary, a decrease in COVID-19 cases and deaths resulted in a higher number of daily trips. More importantly, the authors found the distance did play an important role in understanding residents’ travel behavior. Specifically, daily trips for short distances changed promptly in response to the changes in COVID-19 cases and deaths. On the other hand, the medium and long trips tend to change slowly, and there is a time gap between the observation of COVID-19 development and changes in daily trips for those distances.

Based on those findings, it appears that residents’ transportation mode choice depends on their travel behavior. They tend to make their travel decisions and travel distances based on what they observe of COVID-19 infection and severity. For example, when they notice a decrease in COVID-19 new cases and deaths, they immediately increase the daily short trips, either to go to work, groceries, or restaurants. As they make more short trips, they feel safer and more comfortable making more medium and long trips (Beck and Hensher, 2020; and Truong and Truong, 2021). Accordingly, it is logical to argue that the more daily medium and long trips the residents make, the more likely they choose to travel long distances by air. In other words, daily trips with medium and long distances could be good indicators for air travel. These are

![Fig. 3. Number of people checked in at U.S. airports in 2019 and 2020 (BTS, 2020a).](image-url)
novel variables included in this study to capture residents’ dynamic travel behavior in responding to the stochastic changes in COVID-19’s trend. These input variables would help overcome the difficulties in predicting air travel given the unexpected socio-economic system disruption that we have never experienced before.

In addition to daily trips by distance, more variables were selected in the model to increase the prediction accuracy. In order to evaluate the impact of the economic condition on air travel, the Weekly Economic Index (WEI) is included in the model as another input variable. This variable measures changes in the economy in 2020, collectively. It is consistent with the role of economic condition in current findings in the literature. Furthermore, COVID-19 variables are selected to evaluate how changes in the pandemic would change air travel volume. Specific variables include COVID-19 new tests, new cases, new hospitalized, and new deaths. Finally, travel restrictions in the U.S. and other countries are also included as predictors.

Overall, this paper adds significant value to the air travel literature by investigating the roles of those novel variables. Neural network models can determine how the variables contribute to air travel prediction. Simulation models and sensitivity analysis can estimate the values of air travel during and post COVID-19 in different what-if scenarios. The models also is also scalable and can be used as a decision making tool for the federal government and airlines.

3. Methodology

3.1. Data description

In this paper, data were collected from multiple sources, as presented in Table 1. Air travel data was collected from BTS Commercial Aviation Departure data, which includes the number of commercial aviation departures in the U.S., domestic and international, by day (BTS, 2020c). Thus, domestic and international air travel is measured by domestic and international commercial flights per day, respectively.

Data for daily trips by distance in the U.S. were extracted from BTS Daily Travel During the COVID-19 Pandemic data (BTS, 2020d). Trips are defined as “movements that include a stay of longer than 10 min at an anonymized location away from home; a movement including multiple stays of longer than 10 min before returning home is counted as multiple trips.” The data was collected by the Maryland Transportation Institute and Center for Advanced Transportation Technology Laboratory (CATT) at the University of Maryland from a mobile device data panel merging data from multiple sources. The generalizability of the data is ensured by using a multi-level weighting method to expand the sample, so the results are representative of the entire population in a nation, state, or county (BTS, 2020d). In this study, data of daily trips from March 1, 2020, to December 12, 2020, was used for analysis. Specific variables include the total of daily trips, population not staying home, and daily trips for medium and long distances, from 50 miles to more than 500 miles. Due to the focus on residents’ daily trips at the national level, the dataset was consolidated at the national level, which results in 287 rows. All variables are numeric in the ratio scale.

Additionally, WE data was collected from the Federal Reserve Bank of New York data source. The WEI is “an index of ten indicators of real economic activity, scaled to align with the four-quarter GDP growth rate.” (Federal Reserve Bank of New York, 2020). It measures consumer behavior, the labor market, and production in the U.S. More specifically, consumer behavior is measured by Redbook same-store retail sales index and the Rasmussen Consumer Index. Additionally, labor market condition is measured by initial and continuing unemployment insurance claims, American Staffing Association Index of temporary and contract employment, and federal tax withholding data from Booth Financial Consulting. Finally, production is measured by U.S. steel production from the American Iron and Steel Institute, U.S. electricity output data from the Edison Electric Institute, fuel sales based on Energy Information Administration data, and total railroad traffic from the Association of American Railroads (Lewis et al., 2020). Since WEI is the weekly data, we used the same WEI score for seven days of the same week in the

### Table 1

| Data sources | Variables | Description | Scale | Role |
|--------------|-----------|-------------|-------|------|
| BTS Daily Travel During the COVID-19 Pandemic data (BTS, 2020d) | Population not staying home | Number of residents not staying home | Numeric, ratio scale | Input |
| | Total number of trips | Total number of trips made by residents | Numeric, ratio scale | Input |
| | Number of Trips 50-100 | Number of trips by residents greater than 50 miles and shorter than 100 miles (50 ≤ trip distance < 100 miles) | Numeric, ratio scale | Input |
| | Number of Trips 100-250 | Number of trips by residents greater than 100 miles and shorter than 250 miles (100 ≤ trip distance < 250 miles) | Numeric, ratio scale | Input |
| | Number of Trips 250-500 | Number of trips by residents greater than 250 miles and shorter than 500 miles (250 ≤ trip distance < 500 miles) | Numeric, ratio scale | Input |
| | Number of Trips≥500 | Number of trips by residents greater than 500 miles (trip distance ≥ 500 miles) | Numeric, ratio scale | Input |
| Federal Reserve Bank of New York (2020) | Weekly economic index (WEI) | Index of weekly indicators of real economic activity | Numeric, ratio scale | Input |
| COVID Tracking Project data (2020) | New Cases | Number of new COVID-19 cases reported per day | Numeric, ratio scale | Input |
| | New Tests | Number of new COVID-19 tests reported per day | Numeric, ratio scale | Input |
| | New Deaths | Number of new COVID-19 deaths reported per day | Numeric, ratio scale | Input |
| | New Hospitalized | Number of new COVID-19 hospitalized reported per day | Numeric, ratio scale | Input |
| Moreland et al. (2020); U.S. Department of State (2020) | Domestic Restrictions | Changes in the travel restrictions u the U.S. | Nominal | Input |
| U.S. Department of State (2020) | International Restrictions | Changes in the travel restrictions u the U.S. and globally | Nominal | Input |
| BTS Commercial Aviation Departures data (BTS, 2020c) | U.S. domestic flights | Number of domestic commercial flights in the U.S. | Numeric, ratio scale | Output |
| | U.S. international flights | Number of international commercial flights in the U.S. | Numeric, ratio scale | Output |
Finally, data for COVID-19 variables were collected from the COVID tracking project data (COVID Tracking Project, 2020). This data source is the primary source used by Centers for Disease Control and Prevention (CDC) to track COVID-19 infection and severity (COVID Tracking Project, 2020). Four COVID-19 variables used in this study include new daily tests, new daily cases, new daily deaths, and new daily hospitalized. The data was collected from March 1, 2020, to December 12, 2020, to match the timeline for daily travel data. Note that the COVID-19 dataset reflects the reported numbers on a specific day but not actual numbers occurring in real-time. This lapse is due to the lead time in the testing procedure and the new deaths and hospitalized reporting system. Regardless, this lapse does not affect the results of this study because residents’ travel behavior changes according to their view of COVID-19 infection and severity based on the reported numbers on the Internet and media (Truong and Truong, 2021).

Domestic and international restrictions variables are measured by a nominal scale, representing the changes in the travel restrictions, domestically and internationally. The following describes the levels of those two variables, determined based on the changes of travel restrictions policies by countries in the world (Moreland et al., 2020; U.S. Department of State, 2020).

Domestic Restrictions.

1. Stay-home-orders: nation-wise stay-home-orders in 42 states: from 03/01/20 – 05/31/20
2. Reopening: phased reopening in many states, given certain travel restrictions: from 06/01/20 – 08/05/20
3. Travel allowed: more states reopening; lift of Global Level 4 Health Advisory; mandatory quarantine after travel is still in effect: from 08/06/20 – 11/02/20
4. Mandate easing for domestic travel: domestic travel restrictions were lessened to accommodate travel demand during the election: 11/03/2020 – 12/12/2020

International Restrictions.

1. Initial lockdown: initial stay-home-orders in several U.S. states; U.S. travel restrictions to Europe; lockdown in many countries in Europe (e.g., Italy, France, Germany, Spain, Denmark, Ukraine, Poland, Czech, Turkey, Hungary, Russia, and other countries, including China, New Zealand, Egypt): from 03/01/20 – 03/18/20
2. Full global lockdown: U.S. State Department issued Global Level 4 Health Advisory: Do Not Travel; more countries on the lockdown, including UK, India, Australia, Zimbabwe, Nigeria, Japan, Korea, Thailand, and more; travel restrictions tightened in many countries: from 03/19/20 – 08/05/20
3. Border reopening for international travel: lift of Global Level 4 Health Advisory, international travel started resuming with mandatory screening and quarantine: from 08/06/20 – 09/08/20
4. Lessened global restrictions: the U.S. stopped screening international arrivals for COVID-19, other countries allowed international travel under strict restrictions: from 09/09/20 – 10/28/20
5. Mixed global travel restrictions: Travel restrictions by the U.S. and some countries continued to be eased in some regions; European countries extended their states of emergency: from 10/29/20 – 12/12/20

3.2. Neural network model

Neural network method was selected to develop a predictive model for air travel in the U.S. A neural network mimics the human brain’s biological neural network to construct the relationships between input and output variables (Haykin, 2009; Tuffery, 2011). This machine learning algorithm is an appropriate method to explored non-linear, complex relationships between inputs and output variables. It is not subject to strict statistical assumptions, such as normality, and is not limited to given inputs. In a neural network structure, hidden layers are used to connect input and output variables to identify hidden patterns in the data (Tuffery, 2011; Sarma, 2013; Truong and Choi, 2020). Given the unknown relationships between predictors and the target variable, neural network is a more appropriate choice than other multivariate statistical methods since it is able to explore new patterns and can detect nonlinear relationships. The use of multiple layers also allows us to discover complex relationships among variables.

In this paper, we constructed the neural network using the multilayer perceptron (MLP) method. It is a feedforward neural network capable of solving problems stochastically and producing approximate solutions for complex problems (Tuffery, 2011; Sarma, 2013). Fig. 4 presents a neural network architecture with two hidden layers, with an input layer, two hidden layers, and an output layer. Each node represents an artificial neuron in the network. For each pair of nodes, there is an input node, an output node, and node bias \( \theta \). In each of the hidden and output layers, there are artificial neurons interconnected via synaptic weights (\( w \)). These weights are calibrated through a training process with input-output data (Haykin, 2009).

The following equations (1)–(3) present formulas for calculating the value of each node at hidden layers and the output layer

\[
H_i = f(\theta_i + \sum_i w_i I_i) \quad (1)
\]

\[
H_{2k} = f(\theta_{2k} + \sum_i w_i H_i) \quad (2)
\]

\[
AV = f(\theta_{AV} + \sum_i w_i H_{2k}) \quad (3)
\]

where:

\( I_i \) is input variables; \( i \) is 1–12 representing twelve input variables: 6 daily trip variables, 4 COVID-19 variables, WEI, and travel restrictions (see Table 1)

\( H_j \) is Hidden layer 1; \( j \) is the number of nodes in this layer

\( H_{2k} \) is Hidden layer 2; \( k \) is the number of nodes in this layer

\( w \) is synaptic weight used in the functions for each node

\( \theta_{AV} \) is the output variable, the number of daily commercial flights in the U.S.

\( \theta \) is bias for each node

In neural network, activation functions are used to formulate the output node and hidden nodes. The most common activation functions are identity, hyperbolic tangent, and sigmoid (Figs. 5–7) (Haykin, 2009; Vieira et al., 2017). Hyperbolic tangent function can be with the range [-1; 1], while sigmoid can be with the range [0; 1]

\[
f(y) = y \quad (5)
\]

\[
f(y) = \tanh(y) = \frac{e^y - e^{-y}}{e^y + e^{-y}} \quad (6)
\]
\[ f(y) = 1 + \frac{1}{1 + e^{-y}} \]  \hspace{1cm} (7)

Three methods for standardization or normalization can be used for input and output nodes: standardization using z-score (Equation (8)), normalization using max and min values (Equation (9)), and adjusted normalization using the adjusted value of the normalization (Equation (10)). The normalization produces values between 0 and 1 and is used with the sigmoid activation function. The adjusted normalization produces values between \(-1\) and \(1\) and is used with the hyperbolic tangent activation function (Haykin, 2009).

\[ x' = \frac{x - \overline{x}}{s} \]  \hspace{1cm} (8)

\[ x' = \frac{x - \text{min}(x)}{\text{max}(x) - \text{min}(x)} \]  \hspace{1cm} (9)

\[ x' = \frac{2^s(x - \text{min}(x))}{\text{max}(x) - \text{min}(x)} - 1 \]  \hspace{1cm} (10)

where.

- \(x\) is an actual variable
- \(x'\) is the new variable
- \(\overline{x}\) is the mean value
- \(s\) is the standard deviation

With a continuous output variable, sum-of-squares error and relative error can be used to evaluate the neural network model performance (Equations (11) and (12)). While the sum-of-squares error captures the variance in the prediction, the relative error captures the predictive power, i.e., the ability to explain variances in the target variable by the predictors.

\[ \text{Sum of Squares Error} = \sum (O_i - P_i)^2 \]  \hspace{1cm} (11)

\[ \text{Relative Error} = \frac{\sum (O_i - P_i)^2}{\sum (O_i - \overline{O})^2} \]  \hspace{1cm} (12)

where.

- \(O\) is the observed value
- \(\overline{O}\) is the mean value
- \(P\) is the predicted value

The neural network was constructed in an iterative process. First, the data was partitioned randomly into training and validation samples in

![Fig. 4. Neural network architecture.](image-url)
the ratio of 50/50; 50% of the data was used to validate the model. The purpose of random splitting is to ensure the reliability and generalizability of the model (Tufferi, 2011; Sarmar, 2013; Truong et al., 2018; Truong and Choi, 2020). The minimum and the maximum numbers of nodes in the hidden layers were then selected along with the number of hidden layers to perform the optimization algorithm to find the best network structure. Activation functions for the output layer and hidden layers could be changed to improve the model performance. Batch training was used to train the model by using information from all records in the training dataset. This method could minimize the total error and usually work effectively with smaller datasets. The training stopping rule was maximum steps without a decrease in error; i.e., the training would be stopped if there was no decrease in error after ten steps.

3.3. Monte Carlo simulation model

Once the neural network structure was found with a good model performance, Monte Carlo simulation was built using the neural network mathematical model. Monte Carlo simulation is a mathematical method that estimates possible outcomes of uncertain events based on the mathematical relationships between the output and inputs and the probability distributions of the inputs (Robert and Casella, 2004; Woo et al., 2020). This method is a stochastic method that can handle uncertainty and calculate the outcomes repeatedly using a different set of random numbers. It also allows us to perform sensitivity analysis to see how the outcomes change in different scenarios.

The following process was used to perform Monte Carlo simulation and sensitivity analysis.

1. Determine probability distributions for input variables
2. Generate random numbers
3. Calculate the values for input variables based on the random numbers and probability distributions
4. Calculate the outcomes using the neural network mathematical model with activation functions and synaptic weights found in the previous section
5. Repeat steps 2-4 with 100,000 trials; stop the simulation when the confidence interval of 95% is achieved
6. Select variables of interest and form scenarios with the specific intervals for these variables
7. Run the simulation again for each scenario
8. Compare the outcomes across scenarios

The Monte Carlo simulation and sensitivity analysis can provide us with useful information to answer the research questions. Specifically, we can find out which inputs are more important in predicting the air travel, correlations between inputs and the output, and how the air travel volume changes from one scenario to another scenario.

4. Results

4.1. Descriptive statistics

Table 2 presents the descriptive statistics for both input and output variables, including mean, standard deviation, minimum, and maximum. Figs. 5 and 6 show the trend of COVID-19 new cases, new tests, new deaths, and new hospitalized over time. It appears that COVID-19 infection had gotten worse towards the end of 2020. While the mean of new cases is about 55,651 cases per day, new cases raised to more than 234,000 cases per day in December 2020, a record number. The daily tests continued to increase given the increased travels at the end of 2020, with about 2 million tests per day. Similarly, while the mean of new deaths is about 1000 deaths per day, we experienced almost 3164 deaths per day in late December 2020. Finally, the daily hospitalized had been fluctuating with an average of more than 2000 hospitalized per day, with two notable peaks in late May 2020 (more than 17,000 new hospitalized) and late October 2020 (about 15,000 new hospitalized). The average number of new hospitalized continued to increase towards the end of the year, with about 4000 daily hospitalized in late December 2020.

Figs. 7–9 show the population not staying home, the total number of trips made by U.S. residents per day, and daily trips by distance. It appears that about 75% of the U.S. population had chosen not to stay home. This number increased a little bit from 80% since March 2020. It is worth noting that the number did not decrease much in December 2020. Thus, despite a high COVID-19 surge at the end of 2020, people still decided to go out. As shown in Fig. 8, the total trips increased

Fig. 5. New COVID-19 cases and tests in 2020.
slightly in late May 2020, then decreased in early July 2020. Since then, the total trips had not changed much, with about one billion trips per day. If we look at daily trips by distance (Fig. 9), it appears that considering trips greater than 50 miles, about 70% of the trips are between 50 and 100 miles, followed by trips between 100 and 250 miles (about 20%). The frequency of trips greater than 250 miles is lower, with

| Variables                | Minimum      | Maximum      | Mean          | Std.Deviation |
|--------------------------|--------------|--------------|---------------|---------------|
| Trips50-100              | 8,559,832    | 25,539,735   | 19,257,694.98 | 2,904,221.66  |
| Trips100-250             | 4,338,784    | 14,476,977   | 8,561,431.82  | 1,666,380.37  |
| Trips250-500             | 987,829      | 3,651,375    | 1,840,907.28  | 471,200.37    |
| Trips>500                | 316,759      | 5,901,062    | 1,004,558.47  | 793,705.37    |
| TotalTrips               | 672,104,143  | 1,312,174,388| 971,041,618.99| 100,299,335.02|
| PopulationNotStayingatHome| 216,955,650  | 271,777,284  | 243,663,530.41| 9,289,566.35  |
| WEI                      | –11.45       | 1.42         | –6.98         | 3.24          |
| NewDeaths                | 1            | 3164         | 1008.87       | 657.16        |
| NewHospitalized          | 0            | 17,287       | 2160.02       | 1818.19       |
| NewCases                 | 24           | 234,817      | 55,651.36     | 51,009.55     |
| NewTests                 | 109          | 2,209,525    | 756,194.39    | 512,205.53    |
| USDomesticFlights        | 6679         | 29,042       | 14,739.15     | 4577.04       |
| USInternationalFlights   | 326          | 4694         | 1158.01       | 877.49        |

Fig. 6. New COVID-19 deaths and hospitalized in 2020.

Fig. 7. Population not staying at home in 2020.

Table 2
Descriptive statistics of input and output variables.
Fig. 8. Total number of trips in 2020.

Fig. 9. Daily trips by distance in 2020.

Fig. 10. Weekly economic index (WEI) in the U.S. in 2019 and 2020.
about 6% between 250 and 500 miles and 4% greater than 500 miles.

Finally, Fig. 10 shows the trend of WEI in 2019 and 2020. It seems that before the pandemic, WEI was about 2 points. Then it decreased significantly with the impact of COVID-19. The lowest WEI was 11.45, observed in later April 2020. The average WEI from March to December 2020 was –6. However, WEI gradually improved towards the end of 2020, with the WEI of about –2 in December 2020.

| Layer                  | Description                        | Domestic model | International model |
|------------------------|------------------------------------|----------------|---------------------|
| Input Layer            | Number of Units                    | 12             | 12                  |
|                        | Rescaling Method for Covariates    | Standardized   | Standardized        |
| Hidden Layer(s)        | Number of Hidden Layers            | 1              | 1                   |
|                        | Number of Units in Hidden Layer    | 6              | 5                   |
|                        | Activation Function                | Hyperbolic tangent | Hyperbolic tangent |
| Output Layer           | Target Variable                    | U.S. Domestic Flights | U.S. International Flights |
|                        | Rescaling Method for Scale Dependents | Standardized   | Standardized        |
|                        | Activation Function                | Identity       | Identity            |
|                        | Error Function                     | Sum of Squares | Sum of Squares      |

* Excluding the bias unit.
4.2. Neural network results

Table 3 presents the best neural network model for both domestic and international models. The best neural network for the domestic model has one hidden layer and six hidden nodes, while the best neural network for the international model has one hidden layer with five hidden nodes. Both models use hyperbolic tangent as the activation function for the hidden nodes and identity for the output node. The final domestic model has a sum of squared error of 3.073 and a relative error of 0.044. In other words, about 95.6% of the variance in the target variable is explained by the input variables. Additionally, the final international model has a sum of squared error of 1.432 and a relative error of 0.020. In other words, about 98% of the variance in the target variable is explained by the input variables. Thus, both models have a good prediction accuracy. Figs. 11 and 12 present the predicted by observed chart and residual by predicted chart, respectively, for the domestic model. Similarly, Figs. 13 and 14 present the predicted by observed chart and residual by predicted chart, respectively, for the international model. It seems that the prediction is fairly accurate with a very small marginal error. In addition, the residual by predicted charts do not show any patterns or trends, such as linearity (straight line) or non-linearity (curve), indicating good model fit was achieved for those models (Tuffery, 2011; Sarma, 2013; Hair et al., 2018). Accordingly, the neural networks were considered valid and accurate, and the mathematical models were used to build the simulation model for both U.S. domestic and international flights.

The variable importance charts for both models are shown in Figs. 15 and 16. The chart was created by performing a sensitivity analysis to estimate the importance of each predictor in determining the neural network. The charts present the importance and normalized importance of those predictors. For the domestic model, it appears that WEI is the most important predictor for air travel, followed by trips between 50 and 100 miles, trips between 250 and 500 miles, trips between 100 and 250 miles, and new cases. On the other hand, new tests, trips greater than 500 miles, and total trips are among the least important predictors. Domestic restrictions seem to be moderately important compared with other variables. As for the international model, WEI is also the most important predictor, followed by new cases, new tests, trips between
100 and 250 miles, and international restrictions. On the other hand, the least important predictors include trips greater than 500 miles, total trips, and trips between 50 and 100 miles. Thus, it appears that the travel restrictions are more important to international flights than domestic ones.

4.3. Monte Carlo simulation results

Monte Carlo simulation models were built and run for both domestic and international flights. First, distributions for input variables were determined by fitting the data to distribution types. Kolmogorov-Smirnov test was used to evaluate the goodness of fit. Table 5 presents the detailed probability distributions and parameter values for all input variables. The results indicate acceptable goodness of fit for these distributions at the 0.01 significance level. Hence, the distributions were used for building simulation models. The neural network structure, synaptic weights, and their mathematical expressions found in the previous section were used to simulate input values and estimate the outcomes. All simulation models were run with a maximum of 100,000 trials, and the simulation stopped when the confidence interval was within a specified threshold. More specifically, the simulations were stopped when the confidence level of 95% was reached with a threshold of 1.0%. The same input distributions and stopping criterion were used in simulations for both domestic and international flights.

Figs. 17 and 18 present the probability density and cumulative distribution of the simulated cases for U.S. domestic flights, respectively. The probability density determines the probability that the output is within a given region. In this case, the probability density shows a probability of 90% that the domestic air travel is between 6555 and 22,347 flights per day. In addition, there is a 5% chance that air travel is either fewer than 6555 or greater than 22,347 flights per day. The cumulative distribution shows a probability of 90% that the air travel is less than 21,002 flights per day and a probability of 10% that the air travel is less than 8408 flights per day.
Figs. 18–20 present the simulation results for U.S. international flights. The probability density in Fig. 18 indicates a probability of 90% that the international air travel in the U.S. is between 391 and 2344 flights per day. The probability that the air travel is either fewer than 391 or greater than 2344 flights per day is 5%. In addition, the cumulative distribution in Fig. 19 shows a probability of 90% that international air travel is less than 1913 flights per day and a probability of 10% that the air travel is less than 500 flights per day.

### Table 5

| Input variables                  | Distributions | Parameter Values |
|----------------------------------|---------------|------------------|
| New cases                        | Weibull       | a 57,316.55      |
|                                  |               | b 1.09           |
|                                  |               | c 0.00           |
| New deaths                       | Normal        | mean 1008.88     |
|                                  |               | stddev 656.01    |
| New hospitalized                 | Normal        | mean 2160.02     |
|                                  |               | stddev 1815.02   |
| New tests                        | Normal        | mean 756,194.39  |
|                                  |               | stddev 511,312.40 |
| Population Not Staying at Home   | Lognormal     | a 243,488,637.74 |
|                                  |               | b 0.04           |
| Total trips                      | Lognormal     | a 966,031,702.81 |
|                                  |               | b 0.10           |
| Trips 100-250                    | Gamma         | shape 26.77      |
|                                  |               | scale 0.00       |
| Trips 250-500                    | Lognormal     | a 1,786,345.51   |
|                                  |               | b 0.24           |
| Trips 50-100                     | Weibull       | a 20,430,756.99  |
|                                  |               | b 8.35           |
| Trips >500                       | Lognormal     | a 841,931.03     |
|                                  |               | b 0.54           |
| WEI                              | Normal        | mean -6.08       |
|                                  |               | stddev 3.23      |
| Domestic Restrictions            | Probabilistic | 1 0.32           |
|                                  |               | 2 0.23           |
|                                  |               | 3 0.31           |
|                                  |               | 4 0.14           |
| International Restrictions       | Probabilistic | 1 0.06           |
|                                  |               | 2 0.49           |
|                                  |               | 3 0.11           |
|                                  |               | 4 0.17           |
|                                  |               | 5 0.16           |

**Fig. 17.** Probability density for daily U.S. domestic flights.
4.4. Sensitivity analysis - what-if scenarios

The simulation models presented in section 4.3 were used to conduct sensitivity analyses to estimate how the outputs, domestic and international flights in the U.S., change in different scenarios. Four scenarios were created to represent different situations during and post COVID-19 pandemic. More specifically, these scenarios were based on the potential economic condition and trend of the pandemic, using different values for WEI and COVID-19 variables. WEI values in the scenarios were determined based on its historical data in the past two years, as shown in Fig. 10, by considering the trend of WEI over time before and during COVID-19. For COVID-19 variables, new deaths and new hospitalized were selected since they better represent the severity of the pandemic than new cases and new tests. The values for COVID-19 variables were determined based on the Institute of Health Metrics and Evaluation’s (IHME) forecast predicting COVID-19 new deaths and new hospitalized in 2021 in different scenarios (IHME, 2021). In the sensitivity analysis, daily travel variables were used as uncontrollable inputs since their values depend on residents’ dynamic travel behavior rather than the government policies. The values of these variables in the analysis were generated based on the distributions and parameters, as presented in Table 5. Their contributions to air travel volumes are determined based on the synaptic weights of the neural network models.

These four specific scenarios are presented in Table 6. Scenario 1 represents the easing of restrictions and mandates during COVID-19, while the vaccine rollout is very slow. Residents will face very minimal to almost zero restrictions regarding social distancing, facial covering, indoor dining, and gathering in a big group without being protected by vaccines. It is considered the worst-case scenario, given the continued surge of COVID-19 cases and deaths in late 2020 and early 2021. The economic situation will worsen, and we will continue to experience a significant surge in new deaths and new hospitalized due to COVID-19. The number of new tests and new cases will be a record high as well. Scenario 2 represents the situation with the moderate restrictions, which include mask mandate to some extent, social distancing, low capacity in-door dining, and prohibition of big events.
Table 6
Four scenarios for the sensitivity analysis.

| Variable parameters | Scenario 1 – Mandate easing, slow vaccine rollout | Scenario 2 – Moderate restrictions, slow vaccine rollout | Scenario 3 – Rapid vaccine rollout | Scenario 4 – End of COVID-19 |
|---------------------|-----------------------------------------------|-----------------------------------------------|------------------------------------|------------------------------|
| WEI                 | –8                                            | –4                                            | –1                                 | 2                            |
| New deaths          | 3000                                          | 1000                                          | 300                                | 10                           |
| New hospitalized    | 10,000                                        | 2000                                          | 800                                | 50                           |

Table 7
Sensitivity analysis for daily domestic flights in the United States.

| Input variables | Parameters | Target: Domestic flights | 95% CI | Percentiles |
|-----------------|------------|--------------------------|--------|-------------|
|                 |            | Mean                      | Std. Dev. | Lower | Upper | 5.00% | 25.00% | 50.00% | 75.00% | 95.00% |
| WEI             | –8         | 13,053.45                | 5050.51  | 12,922.93 | 13,183.97 | 4608.02 | 9406.16 | 13,266.61 | 16,861.34 | 21,029.56 |
|                 | –4         | 17,166.76                | 4586.53  | 16,995.12 | 17,388.40 | 8945.14 | 14,198.26 | 17,692.82 | 20,293.57 | 24,294.92 |
|                 | –1         | 19,933.39                | 3933.64  | 19,734.06 | 20,132.72 | 12,774.51 | 19,779.66 | 22,158.35 | 24,498.05 | 26,445.26 |
|                 | 2          | 21,923.55                | 3175.20  | 21,726.75 | 22,120.35 | 16,549.27 | 19,779.66 | 22,158.35 | 24,498.05 | 26,445.26 |
| New deaths      | 3000       | 12,591.83                | 4094.97  | 12,465.92 | 12,717.75 | 5486.00  | 10,116.75 | 12,371.81 | 15,342.94 | 19,481.78 |
|                 | 1000       | 15,201.68                | 4866.62  | 15,049.69 | 15,353.68 | 6616.64  | 11,833.15 | 15,462.27 | 18,744.14 | 22,780.01 |
|                 | 300         | 16,030.99                | 5003.54  | 15,870.69 | 16,191.28 | 7154.32  | 16,548.17 | 19,693.33 | 23,521.24 |
|                 | 10          | 16,195.31                | 4933.64  | 16,033.49 | 16,352.73 | 7620.90  | 12,741.03 | 16,819.68 | 19,822.84 | 23,629.46 |
| New hospitalized | 10,000     | 14,275.66                | 4962.09  | 14,132.92 | 14,418.41 | 5636.85  | 13,458.78 | 16,548.17 | 19,693.33 | 23,521.24 |
|                 | 2000       | 14,560.53                | 4982.71  | 14,414.93 | 14,706.13 | 5992.30  | 14,746.37 | 18,138.73 | 22,456.70 |
|                 | 500         | 15,124.87                | 4876.26  | 14,973.62 | 15,276.11 | 6549.06  | 15,382.00 | 18,693.71 | 22,712.61 |

Table 8
Sensitivity analysis for daily international flights in the United States.

| Input variables | Parameters | Target: International flights | 95% CI | Percentiles |
|-----------------|------------|-------------------------------|--------|-------------|
|                 |            | Mean                          | Std. Dev. | Lower | Upper | 5.00% | 25.00% | 50.00% | 75.00% | 95.00% |
| WEI             | –8         | 983.79                        | 543.56  | 973.96  | 993.63 | 322.60  | 564.08  | 875.67  | 1288.52 | 1912.10 |
|                 | –4         | 1497.23                       | 682.18  | 1482.26 | 1512.21 | 556.33  | 1030.91 | 1416.52 | 1806.18 | 2927.69 |
|                 | –1         | 1933.90                       | 777.82  | 1914.56 | 1953.24 | 939.11  | 1425.68 | 1771.76 | 2262.83 | 3610.22 |
|                 | 2          | 2385.11                       | 850.56  | 2331.56 | 2378.66 | 1300.42 | 1740.51 | 2047.75 | 2965.98 | 4011.95 |
| New deaths      | 3000       | 1279.92                       | 521.89  | 1267.12 | 1292.71 | 457.48  | 910.50  | 1297.00 | 1608.37 | 1991.69 |
|                 | 1000       | 1214.88                       | 612.19  | 1202.73 | 1227.03 | 404.02  | 755.50  | 1138.24 | 1556.11 | 2374.21 |
|                 | 300         | 1226.64                       | 643.34  | 1214.37 | 1238.90 | 418.88  | 750.90  | 1116.33 | 1545.14 | 2517.06 |
|                 | 10          | 1238.08                       | 653.45  | 1225.70 | 1250.46 | 414.10  | 758.33  | 1124.70 | 1547.45 | 2624.04 |
| New hospitalized | 10,000     | 874.95                        | 293.04  | 866.20  | 883.70  | 366.77  | 658.68  | 912.24  | 1085.57 | 1297.35 |
|                 | 2000       | 1234.85                       | 624.15  | 1222.50 | 1247.20 | 407.78  | 768.68  | 1156.15 | 1579.42 | 2440.71 |
|                 | 500         | 1474.78                       | 759.84  | 1460.03 | 1489.53 | 469.91  | 901.22  | 1373.58 | 1857.84 | 2997.34 |
|                 | 50          | 1564.58                       | 796.93  | 1548.93 | 1580.22 | 468.95  | 961.76  | 1463.07 | 1975.68 | 3138.07 |
| International Restrictions |            |                               |         |          |        |          |        |          |        |          |
| Scenario 1b     | 1169.55    | 590.94                        | 1157.85 | 1181.24 | 381.60  | 755.50  | 1116.33 | 1545.14 | 2517.06 |
| Scenario 2b     | 1198.29    | 584.52                        | 1186.31 | 1210.27 | 416.00  | 777.94  | 1124.70 | 1515.78 | 2925.27 |
| Scenario 3b     | 1316.01    | 636.78                        | 1302.85 | 1329.17 | 449.56  | 864.84  | 1231.05 | 1654.74 | 2582.33 |
The vaccine rollout is still very slow in this situation, indicating minimal protection for the residents. The economy still faces challenges with a high unemployment rate, increased unemployment claims, closeout of many businesses, and reduced GDP. We will continue to see a relatively high number of COVID-19 deaths and hospitalized. The vaccines will be available but very limited, and the rollout will be slow. This is the scenario of our world during COVID-19 that we experienced in early 2021. Scenario 3 represents a positive trend in containing the pandemic, with a rapid rollout of vaccines. In this scenario, a majority of the population will receive two doses of vaccines, as required, without any difficulties. More residents will become immune to COVID-19, which will reduce the number of new deaths and hospitalized. Since there will be people who still wait to be vaccinated or choose not to receive the vaccine, the risk of COVID-19 will remain, but at a much lower level. The economy will start to improve with the opening of businesses and commercial activities. It is a scenario in the medium term, probably late 2021 or early 2022. The last scenario, Scenario 4, represents the end of the COVID-19 pandemic when we reach herd immunity via both vaccination and immunity development in our communities. The pandemic will end, and only a very small number of cases, deaths, or hospitalized will be reported daily. The economy will come back to normal as before the pandemic. It is the best scenario, which may take place in the long term, probably in late 2022 or even in 2023.

For international flights, another variable was added to reflect the travel policies of governments in other countries since these policies may affect the U.S. residents’ decision to travel abroad. More specifically, we look at three scenarios as follows:

- Scenario 1b: Other countries close the border due to the surge of COVID-19 in their regions; travel abroad is not recommended by the U.S. government
- Scenario 2b: Other countries open the border with limited flights and strict restrictions, including safety requirements, COVID-19 negative test results, and quarantine; the U.S. government eases travel restrictions, and international air travel resumes
- Scenario 3b: Other countries allow more international flights but still require safety protocol and quarantine for international travelers; the U.S. government eases travel restrictions and rolls out vaccines quickly

The sensitivity analysis was conducted by changing one input at a time and estimate air travel in that scenario using the simulation models. The results present the number of flights in each scenario with the mean value, standard deviation, lower and upper limits for 95% confidence interval, and percentiles. In addition, the probability density charts are presented as well.

4.4.1. U.S. domestic flights scenarios
The overall sensitivity analysis results for domestic flights are presented in Table 7 and Fig. 21. The results show that domestic flights in the U.S. increase from Scenario 1 to Scenario 4 as WEI increases from -8 to +2. In the worst-case scenario (Scenario 1), the average daily domestic flights are about 13,000 flights per day. This number increases throughout Scenarios 2 and 3 and reaches about 22,000 flights per day in Scenario 4. Note that Scenario 4 is the best-case scenario, in which WEI comes back to the normal value of 2. Thus, as the economic condition improves, domestic air travel continues to increase. In other words, air travel volume is sensitive to the change in WEI. However, note that even the best-case scenario still produces fewer flights than what we had in 2019, which was about 25,000 domestic flights per day. Even if we use the upper value of this number, the daily flights can only reach about 22,000 flights per day. The probability density shows that the probability that air travel reaches 25,000 flights per day is about 17.5%.

As for new deaths, as COVID-19 daily deaths reduce from Scenario 1 to Scenario 4, domestic flights increases. However, as shown in Fig. 21, the increase in domestic flights is much lower than the one for WEI. There is a minimal increase in flights between Scenarios 3 and 4. In the best-case scenario, after the end of COVID-19, the average number of domestic flights is about 16,000 domestic flights per day, which is much lower than the one before the pandemic. Similarly, as for new hospitalized, it appears that Scenarios 2, 3, and 4 produce more domestic flights than Scenario 1. However, the change from one scenario to another is very low. The average number of flights in Scenario 4 is 15,717, which is the lowest compared to the air travel volume in the best-case scenario with WEI and new deaths. Hence, it appears that domestic air travel is less sensitive to the change in new deaths and new hospitalized.

4.4.2. U.S. international flights scenarios
We can notice a similar pattern with international air travel, as shown in Table 8 and Fig. 22. The results indicate that international air travel is very sensitive to the change in WEI. More specifically, international flights in the U.S. seem to increase from an average of 983 flights per day (Scenario 1) to 2355 flights per day (Scenario 4). Thus, when the economy improves, the international air travel volume increases significantly. On the other hand, the changes in COVID-19 new deaths and new hospitalized do not have the same effect on the change in international flights. As for new deaths, the number of international flights actually decreases slightly from Scenario 1 (1279 flights per day) to Scenario 2 (1214 flights per day), but it almost does not change from Scenario 2 to Scenario 4, which is 1238 flights per day. New hospitalized does seem to have a higher effect. The number of international flights increases from 874 flights per day in Scenario 1 to 1569 flights in Scenario 4. As for international restrictions, the number of flights increases slightly from 1169 flights per day in Scenario 1b to 1198 flights in Scenario 2b, which in turn has a higher increase to 1316 flights in Scenario 3b.

Overall, it appears that international air travel is much more sensitive to the change in WEI than the changes in COVID-19 new deaths and new hospitalized. In the best-case scenario (Scenario 4 for WEI), the number of international flights (2355 flights) is still lower than the one in 2019, which was about 4300 flights per day. The probability density shows that the probability of reaching 4300 flights per day is 0.42%.

5. Discussions
The paper focuses on predicting air travel in the U.S. during and post
COVID-19. The results of this study indicate some interesting and new findings. As for domestic air travel, the results show that WEI is the most important predictor, followed by trips between 50 and 500 miles. Population not staying home and two COVID-19 variables (new cases and new hospitalized) can be considered moderately important along with domestic travel restrictions. Thus, when people decide to increase daily trips in medium or long distances for work, business, or personal visits, they will more likely consider traveling by air because they feel safe traveling. However, this decision is usually made in conjunction with the current U.S. government’s travel restrictions and the spread and severity of COVID-19.

The results are somewhat similar for international air travel. The number of international flights is most affected by WEI, followed by COVID-19 new cases, new tests, and international restrictions. The only important daily travel variable is the trips between 100 and 250 miles. Hence, when people make more long distance trips domestically, they feel more comfortable flying within the U.S. but not as comfortable flying internationally. The decision to travel to other countries is highly impacted by the economic condition, COVID-19 new tests, new cases, and current international travel restrictions by the U.S. government and governments of other countries. This finding is explained by the negative COVID-19 test result requirement, quarantine, and safety protocols issued by international travel restrictions policies.

Sensitivity analyses provide useful and meaningful findings regarding how air travel would change with the shifts in WEI, and COVID-19 new deaths and new hospitalized. Four scenarios used in the sensitivity analyses include mandate easing (Scenario 1), moderate restrictions (Scenario 2), rapid rollout of vaccines (Scenario 3), and the end of COVID-19 (Scenario 4). Sensitivity analysis results show that air travel is very sensitive to the change in WEI. The number of domestic flights increases almost 70%, and the number of international flights increases about 140%, from Scenario 1 to Scenario 4. On the other hand, air travel volume is much less sensitive to the shifts in COVID-19 new deaths and new hospitalized, when there is a very small change in air travel volume from Scenario 2 to Scenario 4. Thus, even with an improvement in the pandemic situation, air travel does not improve much by itself. In order to boost domestic air travel, a significant improvement in the economy is needed. For international air travel, international restrictions do have some impact on international travel behavior. The sensitivity analysis results show that as governments of the U.S. and other countries continue to ease the travel restrictions, there will be more international flights, but the increase is very modest (about 12.5%). This finding can be explained by the fact that while other countries allow international travel, their governments still have strict travel restrictions in place. A new and interesting finding from the sensitivity analysis is that the probability of reaching the normal air travel volume right after COVID-19 is very low; it is about 17.5% for domestic air travel and 0.42% for international air travel.

These findings show that improving the pandemic situation alone does not guarantee increasing air travel. We need an improved economy in conjunction with containing the pandemic to boost air travel. Additionally, even in the best case scenario, with a normal economic condition after COVID-19, we can still not reach the normal level of air travel in a short time. It may take several years for U.S. residents to travel by air on the level that can help the airline industry to fully recover and bounce back to normal as before the pandemic. This finding is consistent with the finding by Gudmundsson et al. (2021) in their most recent study.

6. Conclusions and recommendations

The impact of COVID-19 on air travel has been apparent, with a significant decrease in domestic and international flights in the U.S. in 2020. However, how air travel would change during and post COVID-19 is still an unanswered question. As COVID-19 continues to spread and it is uncertain when the pandemic will end, finding the answer to this question will help the government and aviation authorities estimate when the airline industry will fully recover. They also allow airlines to develop appropriate strategies to survive. This paper’s findings contribute significantly to the limited literature on COVID-19’s impact on air travel in the medium and long term. From the theoretical perspective, the paper includes daily trips by distance as novel variables in the predictive model. The results of this paper have proven that residents’ daily trips from 50 to 500 miles reflect their daily travel behavior that changes dynamically in responding to the spread and severity of COVID-19. This travel behavior is a good precursor of their transportation mode choice. In essence, the more daily trips they make in those distances, the safer they feel toward traveling long distance amid the pandemic, which, in its turn, makes them choose to use air transport more for travel. It is worth noting that this impact is higher for domestic air travel than for international one. Since COVID-19 is an unprecedented event, which changes dynamically and unpredictably every day, this finding adds value to the air travel prediction literature. The traditional literature tends to focus on macro and micro factors, assuming that no disruption to the socio-economic system occurs. These models typically work for a more stabilized environment but may not work for the dynamic and uncertain situation we are experiencing amid COVID-19. The discovery of the novel variables indicates an alternative way to predict the change in air travel during and post pandemic.

The results of simulations and sensitivity analysis show that controlling the spread of COVID-19 alone would not improve air travel significantly in the near future. As we move toward the end of the pandemic, changes in the number of COVID-19 deaths and hospitalized are not the primary drivers for air travel behavior. Air travel is more sensitive to the change in WEI. Thus, to increase air travel, we need to combine the control of COVID-19 with the economy’s growth. Even when the pandemic is over, residents and businesses still need to be financially stable to generate more air travel volume. Residents need jobs, and businesses need to be fully reopened with revenue. Another important finding is that it will take several years before air travel will be back to normal as before COVID-19.

The paper also has several practical implications. The findings provide the government and aviation authorities with useful information and understanding of how residents’ daily travel behavior determines their air travel decision in the medium and long term, given the pandemic’s uncertainty. The neural network and simulation models can also be used as useful tools to perform various what-if-scenarios to support the decision making process. The government can use the models in this paper to evaluate how different policies in containing the spread of COVID-19, such as travel restrictions and rapid rollout of vaccines, and improving the economy, such as employment, financial, consumption, and energy policies, would affect residents’ travel behavior and air travel. Airlines can also use the models to predict future air travel in different scenarios to formulate appropriate strategies to survive in the competitive market and achieve full recovery in the shortest time.

The primary challenge with the model is to forecast future values of predictors. The forecast values for WEI can be extracted from the Federal Reserve Bank of New York, and forecast values for COVID-19 variables can be extracted by IHME. These organizations have been providing reliable and valid forecasting based on rich data and robust analytical methods. In addition, Maryland Transportation Institute and CATT lab have been collecting the daily travel data automatically. Time series forecast models can also be used to detect the patterns and forecast future values of the residents’ daily travel behavior. As mentioned above, specific scenarios can be developed based on these forecasts, and the simulation models can be used to predict air travel in these scenarios. Furthermore, the model does not take into account the lead time between the change in residents’ travel behavior and the time of their flights. The challenge with this option is the lack of available data on the individual level since the lead time varies from one to another. Data for actual travel decisions can be obtained by conducting large-scale surveys nationwide.
Another note is that we did not examine causal relationships between COVID-19 and air travel volume or between air travel and economic growth. In other words, we focus on correlations rather than causality. The reason is that this paper aims at examining the impacts of multiple variables in predicting air travel, while a causality study focuses on establishing a causal relationship between two variables of interest or causality between two time series in the long run. Such a causality analysis also requires controlling the effects of other confounding variables. A popular method for that analysis is Granger causality, a non-probabilistic temporal method that examines causality between two variables in different time series.}

**Future research**

Future research can expand the model to include more factors such as time, states of residents’ travel behavior, and changes in airlines’ operations to fully capture the dynamism of the economy post pandemic. Additionally, a recurrent neural network model can be used to model the connection of neurons in a sequential order to reflect the temporal dependency in residents’ travel behavior and how it contributes to the change in air travel volumes. Finally, Granger causality can be used to test causality between COVID-19, air travel demand, and economic growth.

**Authorship statement**

Dothang Truong: Conceptualization, Literature Review, Methodology, Investigation, Software, Formal analysis, Writing- Original draft preparation, Writing - Review & Editing.

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