Designing predictive models for customer recommendations during COVID-19 in the airline industry

Carmen Kar Hang Lee, and Eric Ka Ho Leung

***Abstract*—Although travel restrictions imposed by countries are gradually lifted, the airline industry rebounds only when customers' confidence in air travel is restored. Airlines that generate positive customer recommendations during the pandemic can have a competitive advantage in the post-pandemic environment. This study focuses on the prediction of customer recommendations of airlines during the pandemic. The results show that airline ratings established before the pandemic have weak performance, implying that customer recommendations could be based on other factors that are unique to the pandemic. In addition, COVID-19 travel safety of airlines and sentiments hidden in customer reviews are valuable for predicting customer recommendations. The results also confirm that flight duration affects the predictive powers of airline rating established before the pandemic and COVID-19 travel safety rating of airlines. There are important implications for the airline industry. First, airline ratings established before pandemic is not valuable to predict customer recommendations during COVID-19, underpinning the importance of including COVID-19 travel safety measures as part of the airline evaluation criteria in the future. Besides, COVID-19 travel safety is more relevant to customer recommendations in the long-haul markets. When selecting airlines for evaluation, airline rating organizations can give priorities to airlines that offer long-haul flights.**

***Index Terms*—Airline industry, COVID-19, information efficiency, predictive models, travel safety assurance.**

I. Introduction

THE COVID-19 pandemic is a global crisis [1], resulting in border closures, quarantines and lockdowns [2]. Some countries have imposed entry requirements that request travelers to present negative COVID-19 test results before departure. Yet, many of them still witness a large number of imported COVID-19 cases, suggesting that aircrafts are places where people can contract virus easily. People generally have deep worries about hygiene and the risk of being infected [3]. To restore customers' confidence in air travel, it is important for airlines to implement hygiene and safety measures, such as social distancing, safety delivery systems for food and beverages, and mass disinfectant treatments [4], [5]. The COVID-19 travel safety assurance provided by an airline will impact customers' travel experiences during the pandemic, which will eventually affect customer recommendations of airlines. Consequently, prior tourism research conducted before the pandemic, where COVID-19 travel safety of an airline is not taken into account, becomes insufficient to advance our knowledge of customer behaviors during the pandemic. This highlights the need to update and examine how COVID-19 travel safety of an airline can explain customer recommendations.

There has been an academic consensus that quality service positively affects customer satisfaction and behavior, such as purchase intention and recommendation [6]-[8], which eventually affect profitability [9]. For instance, service disruptions, such as flight cancellations and delays, have negative impacts on customer satisfaction [10]. By constructing a predictive model on customer behavior, companies can discover the undying reasons and develop relevant programs to retain customers [11]. A higher airline rating generally implies a better airline image that has emerged as an important predictor of various behavioral intentions [12]. For instance, according to Skytrax Star Ratings, a 5-star airline implies that the airline has a very high, overall quality performance in terms of airport and onboard product and standards of staff service delivery across airport and cabin service environments. However, the airline ratings that were previously established before COVID-19 do not consider any COVID-19 safety measures taken by the airlines. This raises an interesting question of whether those ratings established before the pandemic are still useful for predicting customer recommendations of an airline. Accordingly, we establish our first research question (RQ1):

- Are airline ratings established before the pandemic useful for the classification of customer recommendations of an airline during the pandemic?

During the pandemic, on the other hand, one of the key operational performance indicators in the airline industry is the extent of travel safety assurance that an airline can provide for their customers. Aircraft cleanliness and hygiene is responsible for travel safety and health security [13]. It is non-negotiable and serves as a fundamental component of service quality [14],

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Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org especially during the current pandemic where people need to minimize their risks of being infected [3]. Cleanliness and hygiene can be controlled by airlines. When customers believe that a service failure, such as inability to implement acceptable COVID-19 safety measures, is controllable, they are likely to experience a higher level of negative emotion [15]. COVID-19 Safety Rating, established by Skytrax, is used as a global benchmark for assessing airline hygiene and safety measures during the pandemic, based on detailed and professional investigation. It allows customers to evaluate the risk of being infected when traveling with an airline during COVID-19. Generally, a lower rating means that the risk of being infected could be higher. Yet, its impact on customer recommendations is not well understood. Accordingly, our second research question (RQ2) is:

- Are COVID-19 travel safety ratings useful for the classification of customer recommendations of an airline during the pandemic?

In the current literature, survey-based studies remain the norm for understanding customer behavior, focusing on customer intentions rather than actual behaviors [12], [16], [17]. Unlike those studies, this study leverages online reviews to identify customer recommendations and focuses on actual behaviors (i.e., explicit recommendations in the reviews), rather than intentions. This offers a relatively unified assessment method to identify customer recommendations, compared with using measurement items in surveys. In general, online reviews are formatted in two ways: numeric review ratings (e.g., the number of stars) and textual reviews. Some researchers use numeric ratings as proxies for the overall perceived service quality [18]. However, this might oversimplify quality measures by assuming them to be unidimensional [19]. On the other hand, textual reviews contain personal narrative of experiences made with the service, offering useful information to uncover the drivers of customer recommendations. Specifically, textual reviews allow us to detect customer sentiments [20]. Accordingly, we formulate our third research question (RQ3):

- Are customer sentiments hidden in the reviews useful for the classification of customer recommendations of an airline during the pandemic?

In addition, this study takes into account the impacts that flight distance might have on customer behaviors. Existing literature suggests that short- and long-haul travels are two distinct markets [21]. Increased flight distance exerts a filtering effect, effectively excluding or disadvantaging certain people from taking part in long-haul travel [22]. As a result, the profile, expectation and subsequent behavior of long- and short-haul travelers are different. Crotts and Reid [23] find that long-haul travelers stay significantly longer in destinations than the other counterparts and their spending in destinations is twice as much as they intended to pay out before they start the journey. Kozah and Kim [24] report that long-haul travelers have a smaller early destination choice set and less variety to bring them to a final decision point, compared to short-haul travelers. These studies adopt a destination-specific focus, examining the impact of distance from the destination through the lens of destination management. For each market, destination marketers can maximize customer satisfaction by taking into account the differences in behavior of travelers. Yet, no research has examined if short- and long-haul travelers also have different expectations and needs of airline service and how this affects classification performance when predicting customer recommendations of an airline. Accordingly, we raise our fourth research question (RQ4):

- Does flight duration (i.e., long-haul and short-haul) affect the predictive powers of airline ratings established before the pandemic, COVID-19 travel safety ratings of airlines, and customer sentiments in the reviews when classifying customer recommendations of an airline during the pandemic?

To answer these research questions, this study builds upon information efficiency theory to design classification models for customer recommendations of airlines. We extend information efficiency theory to the airline context and illustrate a systematic approach to categorizing relevant predictors into weak, semi-strong and strong information, drawing new knowledge of airline customer behavior from an information efficiency perspective. In addition, this study is the first to focus on the predictive power of different forms of information that potentially explains airline customer recommendations. In tourism, customers rely on word-of-mouth to make purchase decisions [25], [26]. As tourism product quality is difficult to evaluate prior to consumption, it is helpful to rely on reviews written by other customers before actual consumption. Song et al. [27] report that airline customers have a high enthusiasm, measured by response rate, for exchanging opinions in online platforms. A higher value and knowledge can be captured if one is capable of processing such a large amount of data [28]. In view of the potential of customer reviews in generating new knowledge, this study leverages online reviews to design predictive models for classifying customer recommendations. By uncovering the various important predictors of airline customer recommendations during the pandemic, our findings provide useful insights that can help the airline industry enhance customer satisfaction, restore customers' confidence in traveling with them, and eventually have their businesses recover from the pandemic.

The rest of this paper is structured as follow. Section II presents the literature review and research hypotheses. Section III introduces the research methodology. Section IV discusses the results and implications. Section V concludes the study and provides future research directions.

II. Literature Review

This study builds upon information efficiency theory as a basis of the research hypothesis. Siering and Janze [29] report that information process mechanisms on online reviewers are similar to how people process information and trade in the financial markets. As in the case of traders, online reviewers also take into account different information when providing product or service evaluation. Therefore, in this study, we borrow the theoretical lens for information process from financial market research and investigate information that reflects online recommendations of airlines.

A. Information Efficiency Theory

Originating from financial economics, information efficiency theory focuses on the question how investors process new information and how markets incorporate the arrival of new information [30]. Its underlying assumption is that stock prices reflect all available information because investors trade based on a specific information. Consequently, it is impossible for investors to beat the market unless they have information that are not utilized by the market. To investigate the extent to which information markets are efficient, Fama [31] categorizes information efficiency into three forms: weak, semi-strong and strong. Weak, semi-strong and strong information efficiencies prevail when stock prices reflect historical information, current publicly available information, and private information, respectively [32].

Generally, historical prices are incorporated in present prices, so future price movements cannot be effectively predicted using historical information [33]. The pattern of incremental prices can be approximated by a random walk specification, and no patterns can be identified from the historical data which would allow prediction. Hence, the predictive power is rather weak if investors predict future prices based on solely historical information. A market is semi-strong efficient when present prices reflect current publicly available information, such as corporate news announcements. In such a market, prices immediately reflect new information once it becomes public knowledge [34]. This implies that prices adjust to publicly available new information rapidly and in an unbiased fashion, such that investors cannot earn excess returns by trading on that information. Nevertheless, in reality, market participants may not act promptly on the information. The lack of an immediate response to the current publicly available information makes it difficult to have the information reflected in the market [35]. As a result, including current publicly available information may lead to a higher predictive power. A market has a strong-form efficiency when the prices reflect private information. This, however, should be impossible because there are legal barriers to private information becoming public, as with insider trading laws. This implies that private information provides additional value for prediction, hence the need to stop insider trading activities in financial markets.

Siering [32] builds upon information efficiency theory to investigate predictors of restaurant health violations. His findings reveal that the predictive performance is the worst when only historical restaurant inspection results are used as predictors and the predictive performance improves when private information extracted from textual reviews is taken into account. Transferred to our research context, historical information corresponds to the airline ratings established before the pandemic, whereas current publicly available information represents the COVID-19 travel safety ratings in response to the current pandemic. Finally, private information includes customer sentiments based on personal air travel experiences. Airline customers process these forms of information and react (e.g., whether to recommend an airline) accordingly.

This study focuses on the prediction of customer recommendations, one of the key outcomes of customer satisfaction [36]. A satisfactory service encounter causes positive recommendations while an unsatisfactory encounter develops negative recommendations. Examining textual reviews written by customers can uncover customers' assessment of recommending the service or not, which can help service providers to address customer concerns to enhance customer satisfaction. Besides, as textual reviews contain personal narrative of experiences made with a specific product or service [37], they become a good source of data for researchers to identify useful features to explain customer behaviors, including customer recommendations. For example, Chatterjee [38] develops regression models to predict airline customer ratings and recommendations based on textual reviews. The results show that sentiments and emotions expressed in textual reviews and quantitative ratings given to various service aspects can be used to explain customer ratings and recommendations. Siering et al. [39] investigate how service aspects evaluated by airline customers in online reviews can be used to predict customer recommendations. They discover that service aspect-specific sentiment indicators drive customers' decisions to recommend an airline and suggest that these factors should be incorporated in a predictive model. Inspired by these studies, we see the merit of harnessing textual reviews to predict customer recommendations for the airline sector and also the relationships of ratings and sentiments with customer recommendations. Drawing upon the information efficiency theory, we propose the following hypothesis:

H1: A classifier taking into account only strong information (i.e., customer sentiment hidden in the reviews) outperforms a classifier taking into account only semi-strong information (i.e., COVID-19 travel safety rating), that outperforms a classifier taking into account only weak information (i.e., airline rating established before the pandemic).

B. Airline Industry in the COVID-19 Pandemic

The COVID-19 pandemic has posed significant and irreversible impacts on tourism [4], [40], [41]. It threatens the survival of airlines, many of which have been facing substantial financial pressure [42], as the demand for daily air travel has been affected significantly [43]. Although local governments have provided financial support for the recovery of the airline sector [44], [45], it is likely that the pandemic will pose long-lasting impacts on airline operations [46].

Recent research has focused on recovery strategies for various sectors. For instance, Bag et al. [47] highlight that firms need to focus on resources to improve their information processing capability. Damij et al. [48] investigate the different data skills required in innovation processes, such as intellectual property processes, and propose an activity-to-skills framework for firms to deal with digitalization accelerated by COVID-19. Paul et al. [49] develop a recovery planning optimization model to manage the impacts of the COVID-19 outbreak for online business operations. Generally, governments play an essential role in the pandemic [50]. In the airline sector, recovery needs to follow travel policies imposed by governments [4]. They are expected to continue fostering a safe travel environment to minimize the possibility of viral transmission in a post-pandemic environment. Budd et al. [51] examine the responses from major European airlines to the height of the COVID-19 crisis. They reveal that reassuring customers that air travel is safe and encouraging them to travel by air again is one of the immediate priorities for airline business and management.

To restore customers' confidence in air travel, various COVID-19 travel safety measures have been implemented by airlines. Examples include disinfecting aircraft with ultraviolet light, touchless technologies at airports, and inflight social distancing [52]. Before the pandemic, an airline was rated mainly on the basis of its front-line product and service quality across the onboard and airport environments. There were no specific assessment items related to COVID-19 safety protocols, such as standards of social distancing, efficacy of cleaning systems, and face mask usage. Although cabin cleanliness would be assessed before the pandemic, measures such as using new techniques for UV sanitization and mass disinfectant treatments were not evaluated. Yet, these measures are considered crucial elements during the pandemic.

On the other hand, some of the health and safety measures have been dismissed by airline operators. For example, a call for leaving the middle seat vacant to maximize social distancing has been viewed as impractical by some airlines [53]. While it is acknowledged that a favorable air travel environment should thoroughly consider the risks to all stakeholders [54], [55], the effectiveness of safety measures implemented by airlines remains an open question. In view of this, Skytrax, an international air transport rating organization, launched the COVID-19 safety ratings covering airlines around the globe to investigate the actual hygiene and safety standards of the airlines as a result of the airlines' COVID-19 safety protocols. With reference to the COVID-19 safety ratings, customers can have a better perception of the travel safety level of airlines.

In fact, the pandemic affects not only airline operations, but also customer behavior [56]-[60]. There are studies showing that flight duration has had an impact on customer behavior since the pandemic. For instance, Graham et al. [61] discover that older passengers who are more vulnerable to COVID-19 are concerned about the risk of contracting the virus when they are onboard, and prefer short-haul flights, such as domestic flights. On the contrary, Bauer et al. [62] argue that longer-haul flights can increase travel safety as this could mean point-to-point connection without passengers switching at hubs. Despite the mixed findings, one cannot underestimate the potential risk for in-flight transmissions [63], which can increase with flight duration. As a result, it is important to take into account flight duration when trying to understand customer behaviors during the pandemic. For instance, customers may have increased concern about the risks of contracting COVID-19 when they have a longer flight, and their recommendations become more related to the travel safety assurance provided by the airline. Based on the literature review, we acknowledge that flight duration has an impact on customer behavior during the pandemic. We postulate that such impact will also be reflected in the predictive power of the inputs that we use for prediction. Hence, we propose the following hypothesis:

H2: The predictive powers of airline ratings established before the pandemic, COVID-19 travel safety ratings of airlines, and customer sentiments in the reviews when classifying customer recommendations of an airline during the pandemic are affected by flight duration.

To summarize, this study is the first that investigates information that reflects online recommendations of airlines through the lens of information efficiency theory, and considers the level of COVID-19 travel safety of an airline, among other predictors, to classify customer recommendations. It advances our current understanding of airline customer behavior, taking into account the impacts posted by COVID-19. Our proposed predictive models can be used as an early warning system that identifies airlines with a high probability of failing on COVID-19 safety protocols. It allows accreditation authorities to prioritize resources for investigations of the measures and standards provided by high-risk airlines, who can then take appropriate countermeasures at an earlier point of time.

III. Research Methodology

The research methodology consists of three phases, as shown in Fig. 1. Phase 1 is Data Collection. Data used in this study include star ratings and COVID-19 travel safety ratings of airlines, as well as customer reviews of the airlines. Sentiment analysis is performed to detect the customer sentiment from the reviews. The sentiment scores obtained will be used as one of the predictors in this study. Phase 2 is to construct different classifiers using various machine learning (ML) algorithms, such as artificial neural network (ANN), logistic regression (LR) and support vector machine (SVM). We categorize the predictors into weak, semi-strong and strong information and use them independently to construct three types of classifiers. Phase 3 is to evaluate the classifiers. We use stratified cross validation and repeat it five times to remove the resampling bias. The classifiers are ranked according to the testing accuracies. We also split the dataset into short- and long-haul groups. Between the two groups, we compare the performance of classifiers. Details of each phase is presented in the following sections.

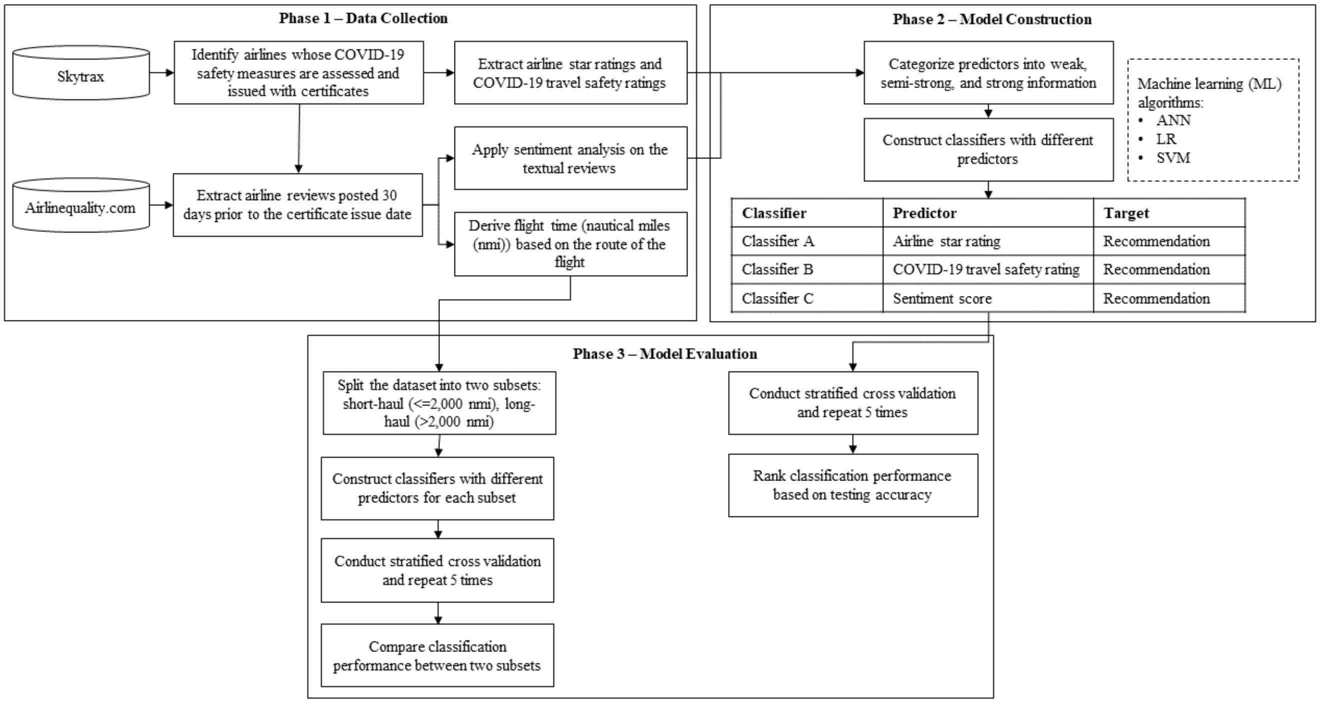

Fig. 1. Research methodology.

A. Phase 1 – Data Collection

The empirical data for this study come from two sources. The first one is Skytrax, an international air transport rating organization established in 1989. The Skytrax Word Airline Star Rating is a global benchmark of airline excellence. For each airline to be analyzed in this study, its star rating is identified. It represents the overall quality standards of the airline. Besides, during the coronavirus pandemic, Skytrax launched the COVID-19 safety ratings covering airlines across the world, providing independent, expert validation of COVID-19 hygiene and safety measures during the pandemic. Based on detailed and professional investigation of actual standards being provided by airlines, the COVID-19 safety ratings award between 3-Star and the highest 5-Star. As of 31 March 2022, 48 airlines have been assessed by Skytrax. This study only considers these airlines that have been assessed by Skytrax because only these airlines have the COVID-19 safety ratings.

After the COVID-19 safety of an airline is assessed, the airline will receive a certificate from Skytrax. We manually download each certificate to retrieve the issue date of the certificate. There are four airlines whose certificates cannot be identified, hence omitted from this study. This leaves us 44 airlines for analysis. Among them, 18 awarded 5-star, 17 awarded 4-star and 9 awarded 3-star.

The second data source for this study is airlinequality.com, which is an independent customer forum for air traveler reviews. For each airline, we retrieve the reviews from the forum. We only consider reviews that are posted 30 days prior to the issue date of the certificate to ensure that the information resembles a recent impression of the airlines, as suggested by Siering [32]. In total, 91 reviews are extracted. In each review, there are attributes including the route of the flight, textual description of the air travel experience, and recommendation. The recommendation attribute is dichotomous where 'yes' represents positive recommendation and 'no' otherwise. It is used as the target of our classifiers. In total, 34% of the customers recommend the airline in their reviews while 66% do not.

The VADER package in Python is used to detect sentiments from the reviews. It is particularly suitable for online user-generated content as it incorporates five heuristics for sentiment analysis, including the use of punctuation, capitalization, degree modifiers, contrastive conjunction, and negations [64]. When detecting the sentiment associated with each review, VADER provides a compound value ranged from -1 to +1. A higher value means a more positive sentiment. The value will be close to -1 or +1 if there are a lot of words, hence VADER works better on short documents. To address this shortcoming, VADER is applied to the reviews at the sentence level, and the overall sentiment of a review is the average sentiment scores of all of its sentences [65].

In addition, we refer to the route for the departure and arrival places associated with each review to calculate the flight duration in terms of nautical miles. Although there is not a universal standard to define long-haul and short-haul travels, Airbus [66] defines long-haul travels as flight with distance longer than 2,000 nautical miles. Smith and Rodger [67] and Skolilová [68] also adopt this definition for their studies. Accordingly, we use 2,000 nautical miles as the cut-off point to categorize long-haul and short-haul flights.

B. Phase 2 – Model Construction

The features used to construct classifiers are categorized into weak information, semi-strong information, and strong information. The airline star rating is considered weak information as its rating system does not take into account COVID-19 safety protocols taken by the airlines. COVID-19 safety rating, on the other hand, is considered semi-strong information. It reflects the overall standard of airline hygiene and safety measures during the current pandemic. The sentiment hidden in the customer reviews is considered strong information as it is based on personal experience.

We construct three types of classifiers to predict whether a customer recommends an airline in his/her review. Classifier A takes into account only the airline star ratings; Classifier B takes into account only the COVID-19 travel safety rating; Classifier C takes into account only the sentiment detected from the reviews. To avoid bias issues, we employ three ML algorithms (i.e., ANN, LR and SVM) to construct each type of the classifiers.

C. Phase 3 – Model Evaluation

Given the sample size used in this study, we evaluate the models with five-fold stratified cross validation. This can avoid overfitting as training and testing are performed on different parts of the dataset. We also repeat the five-fold stratified cross validation five times to remove the resampling bias [69]. After all iterations, the average testing accuracies are calculated to evaluate the predictive performance of the models.

In addition, we investigate how classification differs depending on flight duration. Using 2,000 nautical miles as the cut-off point, we split the dataset into two subsets: short-haul and long-haul subsets. We construct Classifiers A-C using the three ML algorithms for each group. We evaluate them with three-fold stratified cross validation and repeat it five times. The testing accuracies from each subset are compared to examine how the classification performance differs across flight duration.

IV. Results and Discussion

A. Descriptive Analysis

Before constructing the classifiers, descriptive analysis is performed to understand the characteristics of the data. As all the variables except the sentiment score are categorical, we particularly look at their relationships based on their co-occurrences. Fig. 2 is a web diagram showing the relationships between two values of the categorical variables. Each value of the variable is represented as a node while the thickness of the lines is based on the number of co-occurrences between two nodes. A thicker line represents a larger number of co-occurrences. It is observed that the lines are the thickest between two pairs, i.e., ‘Recommended = No’ and ‘covid_safety = 4’, and ‘Recommended = No’ and ‘airline_rating = 3’. This illustrates that reviews with negative recommendations are largely found in 3-Star airlines, or airlines that awarded 4-Star for COVID-19 travel safety.

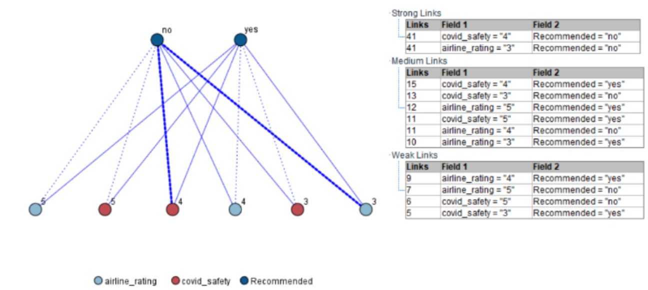

Fig. 2. Web diagram showing the relationships between variables.

In addition, we employ the Apriori algorithm to extract a set of association rules that show the relationships between variables based on their co-occurrences [70], [71]. An association rule is an If-Then rule that can be measured in terms support and confidence. The antecedent support refers to the number of occurrences of the antecedent in the dataset. The confidence of the rule represents the probability of the occurrence of the consequent if the antecedent occurs. The rule support indicates the number of co-occurrences of both the antecedent and consequent. For data understanding purposes, we set the support and confidence thresholds to 15% and 50%, respectively.

Table I lists the association rules obtained when the antecedent is the airline rating established before the pandemic and the consequent is the recommendation outcome. More than half of the reviews (56.04%) are related to 3-star airlines. The numbers of reviews from 4-star and 5-star airlines are comparable (around 20%). If the airline rating is 3-star, then the recommendation is negative with confidence of 80.39%. In other words, the probability of a positive review is 19.61%. Similarly, if the airline rating is 4-star, then the recommendation is negative with confidence of 55%. This means that the probability of a positive review is 45%. On the other hand, if the airline rating is 5-star, then the recommendation is positive with confidence of 63.16%.

TABLE I
Association Rules with Airline Rating as the Antecedent

Antecedent	Consequent	Antecedent Support	Confidence	Rule support
Airline rating = 3	Recommended = No	56.04%	80.39%	45.06%
Airline rating = 4	Recommended = No	21.98%	55.0%	12.09%
Airline rating = 5	Recommended = Yes	20.88%	63.16%	13.19%

Table II lists the association rules obtained when the antecedent is the COVID-19 travel safety rating of airlines and the consequent is the recommendation outcome. If the airline COVID-19 travel safety ratings are 3, 4 and 5, then the probabilities of a review containing a positive recommendation are 29.8%, 26.8% and 64.7%, respectively.

The confidence of the association rules can provide additional insights on the prediction results. For instance, given that COVID-19 travel safety rating is a valuable predictor for customer recommendations, one can refer to the rule confidence to determine the likelihood of the consequent when the antecedent occurs. An airline with a 3-star or 4-star rating in terms COVID-19 travel safety should focus more on improving customer experience as the chance of negative recommendation is high (i.e., above 70%), compared with an airline with a 5-star rating in terms of COVID-19 travel safety. If an airline manages to improve the COVID-19 travel safety rating to 5-star, it can expect that the chance of receiving negative recommendation can be reduced significantly (i.e., 35.29%). Hence, the rule can also help airlines assess the influence of their deployment strategies on customer recommendations when they aim to improve COVID-19 travel safety.

TABLE II
ASSOCIATION RULES WITH COVID-19 TRAVEL SAFETY RATING AS THE ANTECEDENT

Antecedent	Consequent	Antecedent Support	Confidence	Rule support
COVID-19 Travel Safety Rating = 3	Recommended = No	19.78%	72.22%	14.29%
COVID-19 Travel Safety Rating = 4	Recommended = No	61.54%	73.21%	45.06%
COVID-19 Travel Safety Rating = 5	Recommended = Yes	18.68%	64.71%	12.09%

Furthermore, we also verify the VADER model's reliability before using the sentiment scores to construct classifiers. In general, we expect that higher sentiment scores imply higher satisfaction levels, and, in turn, positive recommendations. Fig. 3 shows the distribution of the sentiment scores of the reviews. Reviews that contain positive recommendations mostly have positive sentiments (i.e., with sentiment scores larger than or equal to -0.05, as suggested by Hutto [72]). This shows that our sentiment analysis using VADER is reliable; reviews with positive recommendations generally associated with positive sentiments.

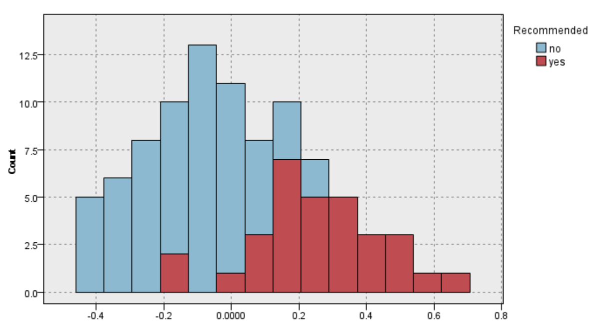

Fig. 3. Sentiment scores and recommendation of the reviews.

B. Predictive Performance of Classifiers

Table III presents the overall predictive performance of classifiers in terms of the testing accuracies. For all the three ML algorithms, the testing accuracies of Classifier A are around 67% and those of Classifier B are around 70%. The accuracies of all Classifier C are the highest and above 85%. We observe that the performance of Classifier C is consistently higher than that of Classifier B, which is higher than that of Classifier A, across all the algorithms. This provides support for our research hypothesis H1.

TABLE III
EVALUATION OF CLASSIFIERS A-C

Algorithm	Accuracy of Classifier A	Accuracy of Classifier B	Accuracy of Classifier C
ANN	66.29%	70.11%	85.32%
LR	66.55%	71.43%	86.86%
SVM	68.11%	71.43%	86.21%

In addition, we investigate how the performance of these classifiers differs depending on the flight duration. Using 2,000 nautical miles as the cut-off point, 47% of the reviews are assigned to the short-haul subset while 53% are to the long-haul subset. As the sample size is smaller after we split the dataset into two subsets, we lower the number of folds in the stratified cross validation to three to allow more instances for training in each iteration. The three-fold stratified cross validation is repeated five times to remove resampling bias. Table IV presents the predictive performance of classifiers in each subset. First, we observe that H1 holds true in both short-haul and long-haul cases. In each case, regardless of the algorithms used, Classifier C has the highest accuracy, followed by Classifier B which is then followed by Classifier A. Across all algorithms, the accuracies of Classifier A and Classifier B in case of short-haul flights are always higher than that of short-haul flights. For Classifier C, interestingly, the accuracies are very similar in both cases. Hence, our results partially support our research hypothesis H2.

TABLE IV
EVALUATION OF CLASSIFIERS A-C IN SHORT-HAUL AND LONG-HAUL FLIGHTS

Flight Duration	Algorithm	Accuracy of Classifier A	Accuracy of Classifier B	Accuracy of Classifier C
Short-haul	ANN	62.35%	69.84%	86.13%
	LR	56.67%	67.46%	87.52%
	SVM	61.75%	68.41%	85.65%
Long-haul	ANN	70.42%	74.58%	84.58%
	LR	70.83%	74.58%	86.25%
	SVM	70.83%	76.67%	85.00%

C. Discussion

In response to RQ1, our results show that using airline ratings established before the pandemic to predict customer recommendations of an airline gives an accuracy of around 67% in average. However, given that in our sample majority of the customers (66%) do not recommend the airline in their reviews, one can simply classify all customers not recommending an airline without deploying any predictive model with an accuracy of 66%. Using this percentage as a baseline, we claim that the airline ratings established before pandemic is not valuable to predict customer recommendations during the pandemic as the resultant accuracies are similar. This underpins the importance of updating and reviewing the relevance of existing airline ratings to the current situation caused by the pandemic.

In response to RQ2, we find that the accuracy is 71% in average when the classifiers take into account the COVID-19 travel safety ratings. This implies that, compared with the airline ratings established before the pandemic, the COVID-19 travel safety ratings are timelier and more relevant to customer evaluation of air travel experiences and recommendations during the pandemic. They have an influence on the classification of customer recommendations. Yet, the improvement in accuracy is only 5%, compared with the baseline.

In response to RQ3, the performance of all classifiers taking into account customer sentiment hidden in the reviews is consistently high, with an average accuracy of 86%. From an information efficiency perspective, the results reveal that online reviews containing private information is valuable for predicting customer recommendations. Specifically, customer sentiments are diagnostic in forming the overall airline recommendations. Compared with the baseline, using sentiment to predict recommendations can increase the accuracy by 20%.

In response to RQ4, we compare the predictive performance of classifiers taking into account flight duration. For Classifier A, the accuracies in both short-haul and long-haul groups are relatively low. This means that airline ratings cannot explain customer recommendations well regardless the time that customers spend in an aircraft. During the pandemic, there are many countries imposing travel restrictions. Customers are left with limited choices for flights. In this situation, they may not choose the airlines based on service quality, airline image or reputation. Instead, their recommendations of the airline could be based on some other factors that are not reflected in the airline ratings established before the pandemic. This potentially explains why the airline rating is not a useful predictor to classify customer recommendations. For Classifier B, the accuracy is higher by 7% in average in case of long-haul flights. This implies that the COVID-19 travel safety ratings are more relevant to customer recommendations when the customers travel long-haul. One explanation might be that the customers perceived the risk of contracting COVID-19 higher when they stay longer in the aircraft. As a result, the extent of travel safety assurance that an airline can provide for their customers becomes more important for long-haul flights, which eventually affects long-haul customer recommendations. For Classifier C, the accuracies are similar between long-haul and short-haul flights. Short-haul and long-haul travelers may focus on different service aspects in their reviews. However, the sentiment scores used in Classifier C are not aspect-based. As a result, even if short-haul and long-haul travelers may have evaluated the airline service differently, the overall sentiment scores detected from the reviews could be the same. Consequently, we cannot see a significant difference in the classification performance of Classifier C.

D. Theoretical Implications

In the current literature, information efficiency theory is largely used in the financial context. This study extends the information efficiency theory to the airline context and uses it to investigate the efficiency of different inputs used in a predictive model. In most predictive models, there are various inputs that possess different levels of information efficiency. Yet, there has not been a systematic approach to define the types of inputs based on their predictive power. Our study illustrates that inputs can be categorized into weak, semi-strong and strong information according to the currentness and personalization. Inputs that are most up-to-date and contain personal experiences have the best predictive power when explaining customer behavior. This kind of inputs can be acquired from textual reviews, implying that predictive models can leverage online reviews to enhance their classification performance.

Furthermore, this study is one of the first that consider temporal perspective of situations (i.e., flight duration) in constructing a predictive model in the airline sector. We investigate the impact of flight duration on the predictive power of various forms of information. In the airline context, we discover that weak and semi-strong information has a higher predictive power in case of long-haul flights. This outlines that classifiers used in the airline sector should specifically consider the impact of flight duration for future research.

Lastly, our findings supplement our existing knowledge of customer behavior in the airline sector by specifically taking into account COVID-19 travel safety. We discover that airline ratings assessed without considering COVID-19 safety protocols taken by airlines fail to enhance the classification of customer recommendation. This implies that predictive models that are constructed before the pandemic require an update before any new knowledge can be drawn to understand airline customer recommendations during the pandemic.

E. Practical Implications

This study uncovers the important information that are valuable for predicting customer recommendations during the COVID-19 pandemic. It provides important implications for both airlines and airline rating organizations.

First, our results show that COVID-19 travel safety and customer sentiments are useful predictors of customer recommendations. During the pandemic, airlines should pay attention to the COVID-19 safety protocols they use and provide sufficient safety assurance for their customers. They can collect feedback from customers regarding the safety measures they use and initiate own safety measures in response to customers' concerns. For instance, Delta Air Lines was the first airline to block middle seats and limit capacity on flights in an effort to curb the spread of COVID-19. The decision was made to promote a safe flying experience by complying with social distancing when the vaccination rate was not high in 2020. It has deepened customers' trust in Delta Air Lines and made many customers decide to choose it for travel during the pandemic. This shows that customers are likely to choose an airline that can promptly respond to customers' concerns with regard to COVID-19 safety.

Even after the airlines receive certificates from the rating organizations regarding their COVID-19 safety, they shall not take this as the end of the process. Especially for airlines whose travel safety measures are not up to standards, they are suggested to take appropriate countermeasures to improve. This is essential not only for restoring customers' confidence in air travel and recommendations of the airlines, but also for curbing viral transmission around the globe, by mitigating the risk of travelers acquiring COVID-19 on flight before entering the community.

Regarding the impact of customer sentiments detected from the reviews have on explaining customer recommendations, airlines should follow up proactively with customers who posted negative reviews. There are various situations showing that one negative customer comment can cause reputational loss and decrease in bookings of airlines. For instance, after United Airlines was reported on Twitter that flight attendants did not wear masks and allowed customers traveling without masks despite the mandatory mask policy, the tweet attracted many attentions from dissatisfied customers.

On the other hand, if the customers are likely to make positive recommendations, airlines can provide them with incentives to act as an advocate for the airlines on social media platforms. For example, they can offer free lounge access and/or vouchers for the customers to use on their next flight after the customers contribute an online review.

Furthermore, our results reveal that the airline ratings established before the pandemic are not relevant nor useful for predicting customer recommendations. Therefore, airline rating organizations can take initiatives to update the ratings by taking into account COVID-19 safety measures taken by the airlines. Besides, when selecting airlines for assessing their COVID-19 travel safety measures, they can give priorities to airlines that offer long-haul flights. This is an important implication because airline rating organizations, such as Skytrax, cannot have every airline assessed as necessary in a timely fashion, due to limited resources. Having clear criteria that support airline selection for assessment can help them allocate resources more effectively. Besides, our result shows that the classification performance increases when the information is more up-to-date and private. Airline rating organizations can deploy our models accordingly and keep track with the performance as a proxy of information efficiency. If the predictive performance of classifiers taking into account the COVID-19 travel safety ratings starts declining, it may be a sign that the ratings become less relevant to the current situation. They can then take this as an alert to review and/or update the assessment and investigation they use for the evaluation. This is an important implication in view of the unpredictability of the pandemic. The effectiveness of hygiene and safety measures might vary from time to time. The assessment performed by them should be responsive to the current situation. Otherwise, the certificates they issue are only a snapshot and fail to resemble current travel safety of an airline.

V. Conclusion

In this study, we employ different predictors to construct classifiers for predicting customer recommendations of airlines during the pandemic. Our results show that airline ratings established before the pandemic is the worst-performing predictor as they are not responsive to the current pandemic. COVID-19 travel safety ratings of an airline can explain customer recommendations better, underpinning the importance of travel safety assurance of an airline during the pandemic. Finally, customer sentiment detected from online reviews is the best-performing predictor, providing evidence that online reviews can be leveraged for designing predictive models for future research. In order to better prepare for future pandemics as well as handle pandemics occurring alongside endemics, airlines can create multiple channels for customers to contribute textual reviews. They can analyze customer sentiments hidden in the reviews to assess whether their response during pandemics or endemics can meet customer expectation. For example, they can create a QR code for customers to scan and leave textual comments at the end of each flight. They can deploy our classifiers to predict if their customers will recommend the travel experience. If the customers are likely to have negative recommendations, airlines can approach them and address their concerns at an earlier point of time before they share negative experiences on public social media platforms. Authorities and airline rating organizations can also use COVID-19 travel safety ratings to construct predictive models. The performance of the models enables them to determine whether the ratings are still relevant to the current pandemic, or it is time to re-evaluate airlines' responses to the pandemic. From the perspective of information efficiency, the predictive performance will decline when the predictors become less timely, indicating the need of re-evaluation.

This study has certain limitations, suggesting that future research should be conducted. First, our study does not consider the impact of expectation disconfirmation bias on classification performance. Customers are more likely to contribute online reviews when their expectation are not met. In this research context, customers who choose low-rating airlines might have low expectations regarding airline service, so they might be less likely to make another negative recommendation. Consequently, this might influence the applicability of the proposed predictive models. Future research can divide airlines into different groups (e.g., 2-3 star, 4-5 star) and construct predictive models for each group independently. This method has been used by Siering [32] to confirm the influence of the expectation disconfirmation bias. Second, our sentiment analysis focuses on the overall sentiments that the customers express in their reviews. In a review, however, customers may mention various service aspects, each of which can be associated with different emotions and sentiments. Future research can integrate aspect-based sentiment analysis and predictive models. For example, cluster analysis can be used to uncover service aspects from the reviews, following by sentiment analysis for each service aspect [73]. It would be interesting to further explore if the sentiment associated with a particular service aspect will have a more significant impact on the predictive performance.

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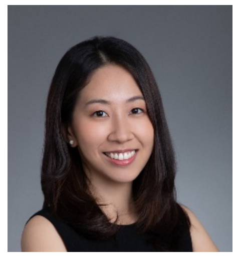

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