



What are the Crucial Factors in Gaining Customer Recommendations in the Airline Industry?

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Abstrak

Bisnis penerbangan terus berkembang. Penelitian ini mencoba untuk mengetahui faktor-faktor penting bagi pelanggan untuk memberikan rekomendasi mereka terhadap sebuah maskapai penerbangan. Pendekatan penambangan teks dan metode pemilihan fitur diterapkan untuk membersihkan kumpulan data dan untuk memilih faktor yang paling penting dari rekomendasi pelanggan. Studi ini mengumpulkan 846 ulasan pelanggan online untuk maskapai layanan penuh dan 179 maskapai penerbangan bertarif rendah. Kebersihan dan kepedulian kru adalah faktor paling penting bagi pelanggan maskapai layanan penuh. Pelanggan maskapai penerbangan berbiaya rendah lebih memperhatikan nilai uang dan informasi penerbangan. Hasil penelitian memberi manajer maskapai wawasan baru untuk membuat pelanggan mereka mau memberikan rekomendasi dan mendapatkan citra merek yang positif.

Keywords: *Ulasan pelanggan online, penambangan teks, rekomendasi pelanggan, pemilihan fitur, maskapai penerbangan*

Abstract

The airline business is continually growing. This study tries to find out important factors for customers to give their recommendations for an airline. Text mining approach and feature selection methods are applied to clean the data set and to select the most crucial factors of customer recommendations. This study collected 846 online customer reviews for full-service airlines and 179 low-cost carrier airlines. Cleanliness and crew care are the most critical factors for full-service airline customers. Low-cost carrier airline customers were more concerned about the value of money and flight information. The results provide airlines' managers with new insights to make their customers willing to give recommendations and gain a positive brand image.

Keywords: *Online customers review, text mining, customer recommendations, feature selection, airline*

INTRODUCTION

The rising number of passengers carried over the past 50 years and the rising number of airlines entering the Indonesian airline market over the past 20 years may both be considered indicators that the country's airline industry is continuing to expand. The number of airline passengers had increased by about 7% every year since 2015, however, the net profit per airline passenger decreased by \$10.1 in 2015, \$6.2 in 2018, and \$5.8 in 2019 (International Air Transport Association, 2020). That is essentially due to intense competition (Y. J. Kim et al., 2020). Fierce competition in the airline industry demands efficient customer relations management either online or offline to bring future income (Riantama et al., 2021). Online customer reviews can be a solution to manage customer relations to know what customers think of the airline. Understanding and sensing consumer perceptions are crucial for corporations to engage prospective consumers with their service or product offerings, particularly in the airline industry. Understanding passengers' experiences are able to help airlines to identify the main factors required to minimize negative intentions and obtain positive post-purchase behaviors (Ban &

Kim, 2019). Moslehpour *et al.*, (2020) have concluded positive reviews about airline products or services noted by consumers making prospective customers generate positive purchasing intentions.

Nowadays, consumers increasingly rely on electronic word-of-mouth (online reviews) as a mechanism to share their perceptions of services or products, particularly in the airline industry (Siering *et al.*, 2018). As such, their purchase decisions are significantly affected by the experience shared by other customers in online reviews (Korfiatis *et al.*, 2019). The basic motivation for customers to resort to online perceptions from others can reduce their information asymmetries and risk about a service or product (Yan *et al.*, 2015). E-WOM shared by other airline passengers is considered widespread, fast, and trustworthy (Brochado *et al.*, 2019). Online reviews have a strong effect on consumers' decision-making processes (Wu & Riantama, 2022).

Besides online customer reviews, customer recommendations within form online reviews are so important to influence the prospective customer decision making process (Orús *et al.*, 2019a). The recommendation of customers of services and products are essential performance indicators for companies to obtain feedback on their offerings (Siering *et al.*, 2018). Consumer recommendations are not only to help consumers at the primary stages of the purchase process by showing new ideas and inspiring them to form primary preferences (Aragoncillo & Orús, 2018). Online customer recommendations are one of the most critical factors in consumers' journey, as consumers trust that the perception of their peers is more trustworthy than those posted by the service provider (Filiari *et al.*, 2015; S. J. Kim *et al.*, 2018; Orús *et al.*, 2019b). On the other hand, expressing unwillingness to recommend has a negative effect compared to not expressing any intention to recommend (S. J. Kim *et al.*, 2018). It is totally bad if customers give not recommended airlines that can decrease their brand image to other customers, and it will influence the business performance. Designing services that surpass or meet customer expectations are the key to the recommendation (Chow, 2015). Knowing which part of the service is needed to be improved is crucial for an airline company to gain customer recommendations.

Nowadays, customers share their stories in online reviews; therefore, it is crucial for businesses to pay attention to this type of e-WOM to comprehend airline customers and determine the variables influencing the recommendation choice (Siering *et al.*, 2018). According to research by (Sotiriadis & Van Zyl, 2013), word-of-mouth (WOM) has a significant impact on customers' subjective norms and attitudes toward an airline as well as their willingness to recommend that airline to others. Online reviews also have an influence on how tourists decide which tourism services to use. In addition to being crucial performance metrics for businesses alone, recommendations and online customer reviews also serve as a vital informational resource for prospective "uninformed" clients (Chatterjee, 2019). When deciding whether to make a purchase, 85% of shoppers rely more on personal recommendations than on online reviews (BrightLocal, 2017). The persuasive power of online product reviews is demonstrated by a recent Nielsen analysis (Nielsen, 2015), which found that consumers trust recommendations or opinions from other customers more than more conventional types of advertising like commercials and product placements in the media.

In order to measure the factors that affect customer recommendations in airlines. Respondents to the survey method may not pay attention to every item or choose answers at random, producing incomplete data (Wu & Riantama, 2022). In order to reduce the unreliability of manufactured responses provided by customers to questionnaire surveys, this study uses online customer reviews (OCRs).

Some researchers have shown how important online reviews and recommendations are to customers before they finalize their decision-making process to choose an airline. It is required that airline companies must know about the most important attributes (factors) that customers care about the most of their service and products through online customer reviews that will impact customer recommendations. Drawing from the literature on impression formation, it is important that researchers further investigate the question of what causes customer satisfaction among airlines' customers. By answering that question, this study tries to find out the crucial factors for customers to give their recommendations or opposites. This study uses online customer reviews to apply an exploratory research to understand customer recommendation factors, and the outcomes can be more reliable. An exploratory research is suitable for this study because we believe that we could not use our past knowledge to judge present problems.

LITERATURE REVIEWS

Understanding customer recommendations through online customer reviews

With the development of social media and the internet, people communicate with others in online communication and create user-generated content (UGC) such as products/services reviews, experiences, opinions, and recommendations (W.-K. Chen et al., 2020). Online reviews are able to influence consumers via systematic or heuristic processing since they are composed of non-content cues (e.g. overall recommendation) as well as content-related characteristics (e.g. argument quality) (S. J. Kim et al., 2018). Online consumer reviews provide customer-oriented information about services and products that work for other consumers as recommendations (negative or positive) about them (Zhao et al., 2015).

Siering et al. (2018) concluded that the airline passengers' opinions of the augmented and core service aspects shared in online reviews show and explain the reviewer's recommendation of an airline. Given the importance of customer engagement, loyalty, and feedback, as mirrored in promoter scores, it is also compulsory to understand the factors that affect positive word-of-mouth, i.e. product or service recommendation (W.-K. Chen et al., 2020), so, it was crucial to investigate the effects of the projected airline quality dimensions on consumers' e-WOM and to provide an overview of important factors which drive negative and positive recommendation of the airlines (Bogicevic et al., 2017). It was confirmed that is critical for researchers and managers to know better to get many good customer recommendations through online reviews.

Online customer reviews

Travelers not only book airline tickets online, but also exchange travel descriptions and information about unpleasant or pleasant travel experiences through personal travel blogs and online review sites (S. B. Kim & Park, 2017). Online customer reviews have become a critical means for both customers and companies to provide and receive feedback concerning services and products (Felbermayr & Nanopoulos, 2016). Nowadays, Customers would like to read online reviews in advance before purchasing products or services. Online reviews have a strong effect on consumers' decision-making processes (Sotiriadis, 2017). The important role of online reviews as an essential data source in tourism has also been shown in recent works that focus on the use of online reviews and their role in affecting decision making and consumer behavior (Rhee & Yang, 2015; Wu & Riantama, 2022).

Some previous researchers have used online reviews in order to know customer voices in many fields of business. Anagnostopoulou et al. (2020) identified which hotel attributes are mostly associated with customer satisfaction through online reviews. Kim et al. (2020) analyzed customer perception by concentrating on the lounge for the airline's differentiated service strategy through the online reviews. Xu (2020) investigated the importance level of the hotel service and product attributes on effecting the opinions of customers of various star levels of editor non recommended and recommended hotels according to their online reviews.

In contrast to administered questionnaires, customer reviews offered evaluations that are able to reflect customer concerns more precisely (Wang et al., 2018). online questionnaires or traditional paper-and-pencil surveys are commonly time-consuming and expensive (Zhou et al., 2016). These traditional research methods demand researchers seek an effective trade-off between estimation performance and the cost of sample collection (Guo et al., 2017). Online customer review sources are deliberated more immense, objective, and without sample bias, since reviews are posted spontaneously without laboratory effects unlike traditional questionnaires (Liu et al., 2017). Online reviews are able to solve some problems that questionnaires face such as being costly in terms of humans, sample bias, and financial resources (Schuckert et al., 2015). This study will use online customer reviews rather than traditional surveys or online questionnaires as a source of data.

Text mining

Instead of dealing with information overload, text mining techniques have been used for online review analysis. These techniques are mostly applied for discovering specific patterns or general trends of online customer evaluations (Yan et al., 2015). Online reviews frequently appear as freeform text and contain a variety of opinions and experiences about various parts of the service being reviewed (Siering et al., 2018). When text mining techniques are applied, freeform review texts are no longer a significant issue.

Text mining has been employed in past studies in a variety of situations, including biomedicine, customer relationship management, tourism, etc., in addition to market surveys. Additionally, past studies in the field of hospitality & tourism research have used text mining to study a variety of topics (K. Kim et al., 2017). 49,080 pairs of restaurant reviews and ratings were looked into as part of restaurant management by (Jia, 2018), who used text mining through a Chinese crowd-sourced online review community to identify main themes, high-frequency phrases, and subtopics. A text mining technique was used by (Lucini et al., 2020) to gauge consumer satisfaction in the airline sector. Through text mining of web reviews, Kim et al., (2020) examined consumer experience of airline lounges. Wu and Riantama (2022) identified which online travel agencies' attributes are highly linked with customer satisfaction through text mining of online reviews.

Text mining brings an effective way to collect and summarize the important issues from a large number of customer reviews accordingly, and customers' essential ideas can be shown more precisely (Xu & Li, 2016). Text mining, also known as intelligent text analysis used a computer-driven automated technique is able to be non-trivial and discover significant patterns of information from unstructured texts (Liau & Tan, 2014). Previous research before used online review data mainly employed the survey method. The survey method is applied since it obtains clear and direct perceptions from customers, but it is limited to collecting a variety of latent opinions and customers' perceptions. Using the text mining method, the limitation of the survey method is able to be overcome by collecting practical perceptions from online customer reviews, it can also help with understanding consumers' underlying latent opinions as well (Hong & Park, 2019). Text mining is able to lower the biases of artificial responses given by consumers to traditional research methods, such as questionnaire surveys and focus groups (Lucini et al., 2020). Particularly for the tourism and hospitality industry, text mining was employed to solve massive business problems by overcoming online consumer reviews, seasonal attributes, and booking quantity (Tao & Kim, 2019).

Feature selection with least absolute shrinkage and selection operator

Feature selection refers to choosing a collection of the most crucial features from a feature subset that can be used for particular tasks (Yuan et al., 2019). Feature selection aims to eliminate irrelevant data to enhance its performance and the scorecard's readability (Kozodoi et al., 2019). A key component of data mining is feature selection, which aims to choose the most pertinent data characteristics and provide more concise and explicit data descriptions. This process benefits from saving time and memory while also helping to build an efficient learning model (H. Chen et al., 2019). The fundamental query is then, which variables (variable/feature selection) should be included in the model (Kostov et al., 2014). On the one hand, feature selection can enhance the performance of the model while also consuming less time and memory. A strong algorithm with good performance will be required to achieve those goals because it is related to what this study needs to obtain the most crucial aspects (words) of airline customers through their evaluations.

In terms of different selection strategies, the feature selection approach can be separated into three categories: embedded methods, wrapper methods, and filter methods (Han et al., 2020). Embedded methods generally display better performance in feature selection (Zhang et al., 2019). The typical method of the embedded approach is Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996). LASSO has advantages better in terms of computational complexity compared to the wrapper technique, and LASSO method is also naturally more accurate than the Convex Optimization (CVX) method (Dastjerdi et al., 2019).

Some previous studies have used feature selection methods with LASSO algorithm in many subjects. Kozodoi et al. (2019) used LASSO to do credit scoring, Uniejewski et al. (2019) employed LASSO to gain statistically sound insights on feature selection and to make recommendations for very short-term electricity price forecasting, and they found LASSO can accomplish with well-performing for feature selection. Sant'Anna et al. (2020) used LASSO feature selection with the purpose of forming portfolios with a reduced number of assets relative to the index for long-short investing strategies. Consequently, this study uses LASSO to get the most important variables (words) from airline customer voices through online customer reviews.

RESEARCH METHODS

Data collection

This study uses Skytrax open website to collect comments (reviews) including the recommendation rating and date review from customer reviews using a crawler tool. Skytrax is a UK-based consultant which works an airport, airline and ranking site review if compared with other websites such as SkyTeam (20 airlines) and Star Alliance (28 airlines), Skytrax has (194 airlines) (Baghirov et al., 2019). Reviews on Skytrax website are considered to be deeply trustworthy seeing that a set of verification and security features is applied (Bogicevic et al., 2017). It gives comprehensive reviews and ratings contributed by customers for over 725 airports and 681 airlines worldwide, being used in preceding studies (Lucini et al., 2020; Xu et al., 2019). Skytrax provides users that can access user-generated information about airlines, and customers can make some reviews their flight experiences. Additionally, the website also gives a chance to customer either give customer recommendations to other or do not give customer recommendations. Consequently, this study takes the airline customer reviews from Skytrax.

The collected reviews were taken from Skytrax taking 4 different airline companies in Indonesia due to they being the biggest airline company in Indonesia based on fleet schedule. Two companies are full-service airline types, and the other two companies are low-cost carrier airline types, four company reviews divide into two different data sets in order to see any differences of customer voices between the two types of airlines. The first data set belongs to full-service airlines, and the second one belongs to low-cost carrier airlines. The data was from April 14th, 2012 - October 6th, 2022. The summary of data sets is shown in table 1.

Table 1. Summary of collected data

Type of Airline	Reviews	Total of Reviews
Full-Service Airline	783	846
	63	
Low-Cost Carrier Airline	140	179
	39	

Source: Data Process ImpotIo (2023)

Data pre-processing

To handle unstructured data sets, RapidMiner studio 9.7 is used in this section (reviews). The tokenize function is used to eliminate any extraneous characters, emoticons, symbols, and words like “on,” “the,” “is,” and “this,” as well as to sort the reviews into lowercase letters. The tokenize function is also used to ignore words with fewer than three letters because they don't contain enough important information. After that, the reviews were tokenized using non-letter separators to break them up into manageable chunks. To connect the single word notions in a token, the stemming approach is used to get at the token's root. For instance, the single token “beauty” is quickly sliced from the two tokens “beautiful” and “beautifully”. Unigram will be used with segment corpuses. Any terms that appear in the dataset less than five times are eliminated using the prune approach. Build the frequency-inverse document frequency to finish (TF-IDF). This preprocessing procedure led to an initial term-by-document matrix TF-IDF of full-service airline data set (of 973×846) and low cost carrier data set (332×179) (Sezgen et al., 2019).

Extract important keywords by LASSO

After TF-IDF was built, Matlab R2017a is employed to run LASSO algorithm to do regression and feature selection simultaneously to obtain the most meaningful words for customer recommendations from the airline customer reviews.

$$\min = \sum_{t=1}^T (y_t - \beta_0 - \beta_1 x_{1,t} - \dots - \beta_k x_{k,t})^2, \text{ s. t. } \sum_{j=1}^k |\beta_j| \leq \lambda \quad (1)$$

According to equation (1), a particular benchmark for penalty selection limits the value of the regression parameter β_i . A transformation that has been k-explained will be used to determine the parameter estimate estimate $\hat{\beta}$ for the key characteristics. The parameter estimation will be impacted by the value of λ . With one exception, the parameter estimate $\hat{\beta}$ is not constrained and the value

calculated using the least-squares method is used when the λ value approaches infinity. Therefore, all parameter estimates are zero when λ is set to 0. As a result, it offers a feature subset based on the coefficient being zero, which is not what we are seeking for in terms of criterion features.

Label the chosen keywords

This stage labels the relevant words identified by LASSO based on the results of the five-fold cross validation experiment and illustrates the frequency significance of each factor. The entire data set can be classified into five reasonable groups. In this section, five-time experiments must be performed to rank those significant terms based on their occurrence frequencies in five folds, which is taken as 5,4,3 appearances, and so on. Each section serves as a testing test, while the remaining four sections serve as a training test. When a topic is more important to the model, it will be mentioned more frequently in the five-fold cross validation trial in terms of word frequency. The more occurrence frequency that words appear, the more significant they are, and the more those words are contained in a particular topic, the more significant the topic is (J. Lim & Lee, 2020). The more occurrence of the words more represent to the model (H. Lim & Kim, 2020).

FINDINGS

LASSO result

The factors with estimated values that are not zero that can be considered as factors which have possible impact to the customer recommendations (Tibshirani, 1996).

Table 2. LASSO experiment result of full-service airlines

Factors	Fold1	Fold2	Fold3	Fold4	Fold5	Frequency
good	0.80399	0.624503	0.932437	1.081867	1.020539	5
crew	0.223509	0.035866	0.337982	0.518333	0.426183	5
call	-0.83902	-0.566	-0.97946	-1.34201	-1.12429	5
dirty	-0.83302	-0.45197	-1.19192	-2.02005	-1.50288	5
result	-1.20097	-0.65963	-1.69468	-2.7772	-2.11044	5
told	-3.18175	-3.01967	-3.29163	-3.44519	-3.35499	5
worst	-3.15903	-2.82341	-3.36778	-3.90781	-3.52694	5
cabin	0.041755	0	0.128292	0.21117	0.175582	4
advise	-0.05368	0	-0.35352	-0.87051	-0.5653	4
chat	-0.00519	0	-0.38722	-1.22557	-0.68119	4
speak	-0.05872	0	-0.49482	-1.25436	-0.83621	4
disgusting	-0.23933	0	-0.77984	-1.96187	-1.22843	4
poor	0	0	-0.0268	-0.50697	-0.23206	3
cancel	0	0	-0.08825	-0.44437	-0.24443	3
compensation	0	0	-0.12819	-0.55725	-0.29161	3
stroller	0	0	-0.11224	-1.06724	-0.48091	3

Source: Data Process Matlab (2023)

Table 3. LASSO experiment result of low-cost carrier airlines

Words	Fold1	Fold2	Fold3	Fold4	Fold5	Frequency
ask	2.347758	2.308058	2.248834	2.308058	2.170179	5
carrier	1.875967	1.79397	1.696352	1.79397	1.583593	5
clean	1.414607	1.344276	1.259669	1.344276	1.172107	5
comfort	1.286623	1.147422	0.989715	1.147422	0.922155	5
crew	1.242682	1.060135	0.95019	1.060135	0.811741	5
delay	1.066108	0.972904	0.874755	0.972904	0.808115	5
drink	1.038148	0.964064	0.844875	0.964064	0.726459	5
easy	0.994554	0.938623	0.826081	0.938623	0.721709	5
fare	0.988728	0.913358	0.819981	0.913358	0.696432	5

feel	0.923269	0.865984	0.814095	0.865984	0.686872	5
fine	0.84697	0.831372	0.784847	0.831372	0.678851	5
food	0.838094	0.737399	0.649013	0.737399	0.670716	5
get	0.62071	0.630908	0.626185	0.630908	0.592991	5
good	0.55804	0.581677	0.618127	0.581677	0.573605	5
great	0.543332	0.558789	0.566239	0.558789	0.558245	5
hour	0.504047	0.414664	0.308625	0.414664	0.185373	5
inform	0.460567	0.348678	0.2281	0.348678	0.098465	5
lcc	0.392127	0.299711	0.196106	0.299711	0.079143	5
limit	0.357343	0.267384	0.177526	0.267384	0.077444	5
low	0.335307	0.220084	0.10851	0.220084	0.024657	5
nice	0.201441	0.16509	0.103227	0.16509	0.018923	5
polite	0.109304	0.046076	0.021697	0.046076	-0.28192	5
poor	0.089894	0.013449	-0.38124	0.013449	-0.31145	5
quick	0.028751	-0.00286	-0.4989	-0.00286	-0.31239	5
smooth	0.008055	-0.13432	-0.52947	-0.13432	-0.50747	5
spacious	-0.01066	-0.44615	-0.53958	-0.44615	-0.56292	5
told	-0.15118	-0.52652	-0.62568	-0.52652	-0.66852	5
wait	-0.36384	-0.61255	-0.7254	-0.61255	-0.80244	5
worst	-0.49839	-0.72872	-0.85611	-0.72872	-0.90171	5
friendly	-0.50959	-0.77208	-0.91896	-0.77208	-0.98994	5
snack	-0.51285	-0.90633	-1.00384	-0.90633	0	4
credit	-0.64435	-0.91203	0	-0.91203	0	3
recommend	-0.79448	-0.93057	0	-0.93057	0	3

Source: Data Process Matlab (2023)

As the results of LASSO, Table 2 showed several important factors with estimated values that are not zero for customer recommendations of full-service airlines. Table 3 showed several important factors with estimated values that are not zero for customer recommendations of low-cost carrier airlines.

Label the Chosen Keywords

Table 4. Factors related to customer recommendations for full-service airlines

Code	Frequency	Words
F1	5	dirty good, result, worst call, told, crew
F2	4	cabin, chat, speak, advise, disgusting
F3	3	poor, cancel, compensation, stroller

Source: Data Process Excel (2023)

Table 5. Factors related to customer recommendations for low-cost carrier airlines

Factor	Frequency	Words
F1	5	ask, carrier, clean, comfort, crew, delay, drink, easy, fare, feel, fine, food, get, good, great, hour, inform, lcc, limit, low, nice, polite, poor, quick, smooth, spacious, told, wait, worst, friendly
F2	4	snack
F3	3	credit, recommend

Source: Data Process Excel (2023)

Table 4 showed keywords related to customer recommendations for full-service airlines;

Factor 1 (Cleanliness and Crew Care): In this factor, customers are concern about cleanliness, and customer may call and tell the crew about that. The main expressions clarify the factors are crew, dirty, call, told.

Factor 2 (Quietness): In this factor, customers are more talk about in the cabin condition in terms of calmness, and customer may be disturbed by someone chat or speak. The main expressions clarify the factors are cabin, chat, speak.

Factor 3 (Flight interruption and Compensation): In this factor, customers focused more about flight cancelation and the problem of getting their compensation. The main expressions clarify the factors are Cancel, Compensation

Table 5 showed keywords related to customer recommendations for low-Cost carrier airlines;

Factor 1 (Value of money and Flight information): In this factor, customers are concern about their value of money of their experience as a low-cost carrier passenger. They also talked about flight and delay information. The main expressions clarify the factors are fare, carrier, low-cost carrier (lcc), comfort, great, poor, information, hour, and delay.

Factor 2 (Food Quality): In this factor, customers mentioned about the quality of food. The main expressions clarify the factors are snack.

Factor 3 (Appreciation): In this factor, customers talked about customer appreciation. The main expressions clarify the factors are cancel, compensation.

DISCUSSION AND CONCLUSION

This study found that cleanliness and crew care is the most important attributes of customer recommendation followed by quietness and flight interruption and Compensation for full-service airlines. This study also found that the value of money and flight information are the most important attributes for customer recommendations followed by food quality and appreciation.

The result shows that LASSO is a powerful algorithm to run feature selection and regression as well. LASSO could get fewer features which can be seen that is the most crucial attributes to influence customer recommendations. (Huang et al., 2017) have confirmed that the results show that a better result can be achieved by including fewer but relatively more important features in a model. LASSO is useful due to choosing the most fitted coefficients in the linear regression (Sant'Anna et al., 2020).

When the critical factors are found by LASSO, labeling factors must be done to get more proper and clear attributes based on their frequency of occurrence. The result shows that full-service airline customers are most affected by Cleanliness and Crew Care to make their recommendation. When those attributes are fulfilled, they will view other factors that are Quietness and so on to Flight interruption and Compensation. It is quite different with low-cost carrier airline customers. They prefer to look Value of money and Flight information in the first place, Food Quality in the second place, Appreciation in the third place as a basis of their recommendation.

This study gives deeper insight to managers and researchers that could get valuable information from customer directly through online customer reviews that have been provided by online travel agency (Expedia) and information gathering website (e.g., Skytrax). Online customer reviews could capture customer opinion deeply since they write the reviews based on their willingness not by forced, so it is more natural that traditional survey (e.g., questionnaire). Online reviews also could be used to decrease sample bias that traditional questionnaire couldn't.

This study also provides to managers to know important factors for customers to recommend their airlines, so those recommendation from customers could be free advertisements that could cut cost and improve company performance if managers know how to deal with the attributes that customers care about. since customer recommendations are one of the most important factors in consumers' decision-making processes, as consumers believe that the opinions of their peers are more reliable than those posted by the service provider (Filieri et al., 2015; S. J. Kim et al., 2018; Orús et al., 2019b).

SUGGESTION

Practical Suggestions

The future research may take reviews from some online travel agency and information gathering website. The future research may also studies airline customer based on their class such as first class, business class and economy class for each category airline because each class may have different needs

of customers. Full-service airline managers may pay attention more to cleanliness and crew care during their services. Low-cost carrier airline managers also need to care about the value of money and flight information.

Theoretical Suggestions

This research could help managers to know more suitable and clearer how to treat their customers by each class. By knowing what customers want from the airlines, airlines can maintain their company performance in terms of profit and brand image.

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