Exploiting User-generated Content for Service Improvement: Case Airport Twitter Data

Lili Aunimo[1] and Luis Martin-Domingo[2]

[1] Haaga-Helia University of Applied Sciences, Helsinki, Finland
lili.aunimo@haaga-helia.fi
[2] Özyegin University, Istanbul, Turkey
luis.martin@ozyegin.edu.tr

Abstract. The study illustrates how airport collaborative networks can profit from the richness of data, now available due to digitalization. Using a co-creation process, where the passenger generated content is leveraged to identify possible service improvement areas. A Twitter dataset of 949497 tweets is analyzed from the four years period 2018-2021 – with the second half falling under COVID period - for 100 airports. The Latent Dirichlet Allocation (LDA) method was used for topic discovery and the lexicon-based method for sentiment analysis of the tweets. The COVID-19 related tweets reported a lower sentiment by passengers, which can be an indication of lower service level perceived. The research successfully created and tested a methodology for leveraging user-generated content for identifying possible service improvement areas in an ecosystem of services. One of the outputs of the methodology is a list of COVID-19 terms in the airport context.

Keywords: social media data mining, topic modelling, sentiment analysis, term extraction, airport services, collaborative networks, content analysis, user-generated content

1 Introduction

Due to digitalization, more and more communication between individuals and organizations is happening in digital channels such as social media. One part of the customer service of many organizations is specifically focusing on such digital collaborative networks, since many people tend to post their feelings about service quality into these environments. The user-generated content available in these social media channels, such as Twitter, may be used to mine a wealth of information concerning a selected service and the entities related to it. This information complements the data obtained through traditional customer surveys and stakeholder analysis. In addition, user-generated contents may provide completely new information as new topics of discussion or new stakeholders, and relations between them, may be discovered – be it customer segments or organizations.

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Collaborative networks consist of autonomous and heterogeneous entities that collaborate to achieve common or compatible goals through interaction that is made possible through computer networks [1]. Airports can be a good example, they have existed for around 100 years now and have evolved from a simple infrastructure, similar to today's bus station, to a complex set of infrastructures with a large number of stakeholders involved and where computer networks play a vital role in the operation. Airport stakeholders are autonomous an heterogeneous and collaborate with one common aim which is to allow passengers to change transport modes and flying to another destination in an smooth and efficient way. The airport stakeholders shown in Figure 1 fall under the category of virtual organization, which is one of the categories of collaborative networks.

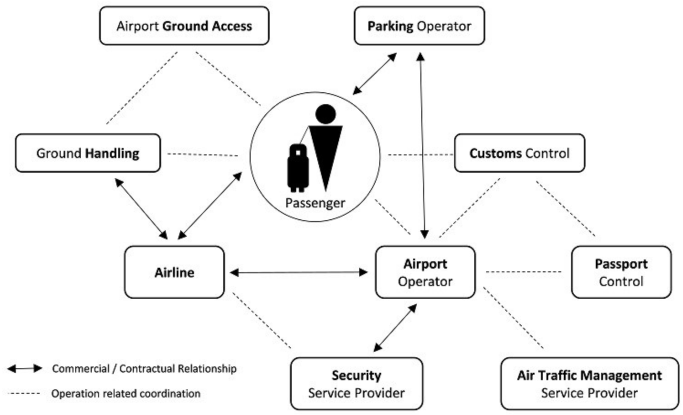

Figure 1: Collaborative network in the airport environment. Authors, adapted from[2].

Social media platforms offer airports novel and efficient ways of communicating and interacting with customers and other service providers. The interaction often deals with topics related to announcements on current issues, customer service, marketing and recruiting, among others [3]. The communication on social media between the passenger and the airport can lead to co-creation activities that produce new value to all participants of the network. Many platforms with user-generated contents are available for such co-creation activities. Some of them are social media platforms (e.g. Twitter, Facebook, Instagram, LinkedIn) and some other are specialized blogs and interactive digital services that enable the collection of customer feedback, such as TripAdvisor or Skytrax (https://www.airlinequality.com/).

User-generated content can be an important source for customer insight creation and for service development [4]. The data is unstructured and in large quantities, which in social media sites typically refers to natural language data that may be ungrammatical, noisy and very concise.

The airport business was chosen as it represents a complex environment, with many different service providers (airport management companies, airlines, luggage handling companies, food & beverage, shops, etc.), for which although measuring passenger perceptions of service quality is difficult [5], it is important as it correlates to the levels of airport reuse and destination revisit [6]. Data from Twitter microblogging service was selected because it has been found to be better than data from some other platforms, such as Skytrax, for collecting information about air passenger experiences [7]. Twitter was also chosen because it is widely used in a professional setting and in the countries under study [1], [8]. Indeed, social media platforms, including Twitter, enable the creation of virtual customer environments where online communities are formed around specific airports and where airport services are discussed. The four years period of the analyzed data (January 2018 – December 2021) was preferred as it allowed studying changes during the COVID-19 pandemic, as it occurred during the last two years of the period under study.

The goal of this research is to define and test a methodology for analyzing user-generated contents to gain insight into the services provided by airport stakeholders forming a collaborative network, from the topics and sentiments mined from the content. The methodology is tested on COVID-19 related tweets concerning 100 airports. It consists of an automatic language detection of tweets, followed by automatic sentiment analysis and topic discovery. Thereafter, tweets are mined to discover novel topic related terms. Finally, the results are evaluated from the point of view of their value for the airport service providers.

With this approach, the study contributes to the data mining and text analytics debate where social media data is leveraged to enhance managerial decision making, for improving airport services and data engineering methods. The study also contributes to the study of airport services, provided by many stakeholders forming a collaborative network, by developing a model for a co-creation process where user-generated contents is leveraged to identify service potential improvements. To the best of our knowledge, this body of research is the first one to apply the theory of collaborative networks to the airport sector.

The rest of the paper is organized as follows. After the introduction, there is a section covering the related literature, followed by the description of the data and methods used. Section 4 presents the main results obtained in the study and section 5 contains an analysis of the results. The last section concludes the study and presents new avenues for future research.

2 Literature Study

Literature covering collaborative networks and the airport sector, to the best of our knowledge, is scant. However, Viri et al., [9] use the model of a collaborative network of multimodal transport services and big data to improve the services provided to drivers and passengers in the Finnish city of Tampere.

Spring et al. (2016) [2] refers to airports as network of interdependent service providers. In the recent pass, they have been promoting structured information sharing among various members of the network through a project that involves a set of practices called ‘Collaborative Decision-Making’ (CDM). For example, at Helsinki’s Vantaa

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Airport and Warsaw Airport, partners are required to share freely operational information like the estimated landing time and actual taxi-in time for each flight.

Graça & Camarinha-Matos (2020) [10] indicate that the sustainability of collaboration is not a given and requires continuous performance improvements. While evaluating a collaborative business ecosystem in IT organizations, they highlighted that well-defined performance indicators can be used to both assess the collaboration level and act as a mechanism to induce an improvement in the collaborative behavior of the participating organizations. This is relevant also in the airport environment.

Social media data is being used more and more in the airport service quality field, which aims to measure air passenger perceptions from different service areas of the airport terminal building. It was originally identified as an important component for the planning and design of the land side of a terminal building [11]. This field of research, accordingly to Barakat et al., [12] can be divided into two dimensions: a) identifying service attributes that represent customer satisfaction by referring to surveys that target aviation experts and / or passengers; and b) measuring service quality based on customer feedback, normally through a questionnaire given to passengers.

The use of questionnaires can be costly [13], time consuming [12] and include a delay, since observations are taken until airport managers are able to implement correcting service measures. User-generated content and text mining has been used more often in service management research [14] and started to be used as an alternative to passenger surveys to measure airport service quality: Bae & Chi [15] as well as Gitto & Mancuso [16] used Skytrax, an airport review website which provides independent reviews by passengers; Lee & Yu [17] used Google reviews; Barakat et al., [12] and Martin-Domingo et al. [4] used Twitter as source of data to measure airport service quality. Lu et al. [7] found that Twitter is a better predictor of service quality than Skytrax.

Twitter data, as one of the user-generated content types, can be useful in identifying new service attributes, relevant to airport passengers. For example, Barakat et al., [12] identified that "prayer rooms" were relevant for passengers at King Khaled airport in South Arabia. Thus, Twitter data provides an opportunity to evaluate service attributes which were not included in surveys. User-generated content has also been used to identify which airport services -related topics are relevant at a given airport and at a given time.

The COVID-19 pandemic has provoked substantial changes to the air transport industry as it resulted in a 66 percent decrease in passengers and an estimated loss of €118 billion 2020 [18]. Thus, airports have been dealing with new situations and a new terminology has appeared when communicating with passengers. Within the healthcare sector, Ma et al. (2021) [19] identified 887 English COVID terms that allow medical professionals to retrieve and exchange information. The present research, as part of the value creation of user-generated contents, aims to contribute with coronavirus terminology in the airport environment. This is needed, because words of a natural language evolve over time. Vocabularies have to be kept up-to-date as new words appear and / or words gain new meanings. For example, the Merriam-Webster

Dictionary added 455 new words only in October 2021. Four of these words were COVID related words: breakthrough (medical), super-spreader, long COVID and vaccine passport [20]. Our aim was to explore what COVID related terms are used in the airport context by passengers.

Topic modeling is a research method that has been used to discover topics and to group and identify terms in user-generated content where the topics are not known beforehand. Some of the topic modeling techniques used in the service quality literature of the travel and tourism industry include: Structured Topic Analysis (STA) in tourism destination marketing [21], non-negative matrix factorization (NMF) in airlines and Latent Dirichlet Allocation (LDA) in hotels [22] and in airports [23]. This research employs the Latent Dirichlet Allocation (LDA) [24] . It is a probabilistic model that considers a tweet as a mixture of topics. Topics in turn are modelled as a distribution of words.

3 Data and Methods

3.1 Data

The Twitter airport dataset used in this research was collected from airport users' tweets from a list of 100 airports around the world. The list of airports corresponds to airports' official Twitter accounts with the largest number of followers in 2016. All of the tweets retrieved, using the Twitter Archive (ctrlq.org), included the Twitter account name (Twitter screen name) of each of the 100 airports. For example, for London Heathrow Airport (LHR), the official Twitter account @HeathrowAirport was used.

A total number of 949497 tweets was collected during the period between July 2016 and March 2022. Using the language recognition software Apache TIKA [25], a total of 592131 tweets were filtered as to handle only tweets in English, which is used as the international language of aviation. The World Health Organization (WHO) declared a Public Health Emergency of International concern on 30 January 2020 [26] and pandemic on 11 March 2020. The dataset was divided into two periods: One before the pandemic (2018-2019) with 202061 tweets and the other during the pandemic (2020 – 2021) with 110023 tweets. The number of tweets was considerably smaller during the later period under study because passenger traffic in the airports was very much decreased because of the pandemics [18]. The process of filtering the original Twitter data set to obtain the two data sets under study is illustrated in Figure 2.

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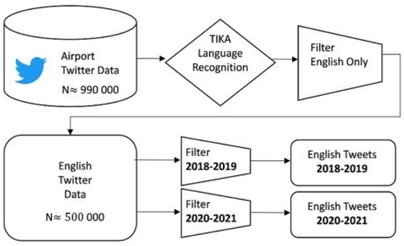

Figure 2: The process of filtering the original Twitter data to obtain the data sets under study.

3.2 Methods

The data sets were processed using the KNIME software [27]. For the sentiment analysis, a lexicon-based method was used. The lexicon applied is derived from the MPQA Opinion Corpus by Maas et al. [28]. The lexicon-based approach assigns sentiment tags to words in a text based on dictionaries of positive and negative words. A sentiment score is calculated for each tweet as defined in Equation (1).

$$Sentiment\ score = \frac{(number\ of\ positive\ words) - (number\ of\ negative\ words)}{total\ number\ of\ words} \quad (1)$$

The topic detection was performed using the LDA (Latent Didrichlet Allocation) method. We used the implementation in KNIME by Newman et al. [29], based on SparseLDA sampling scheme and data structure by Yao et al. [30]. The KNIME node used in our experiments uses the MALLET: A Machine learning for language toolkit [31] . The number of topics is automatically determined using the elbow method. The elbow method estimates the optimal number of clusters (or topics), by running k-means clustering on the data set for different values of k (i.e., different numbers of clusters), and then calculating the within-cluster sum of squared errors (SSE), which is the sum of the distances of all data points to their respective cluster centers as depicted in equation 2.

$SSE = \sum_{i=1}^{n}(x_i - \bar{x})^2$, where n is the number of observations, x_i is the value of the i^{th} observation and $\bar{x}$ is the mean of all observations. (2)

Subsequently, the SSE value for each k is plotted in a scatter chart. The best number of clusters is the number at which there is a drop in the SSE value, giving an angle in the plot. The entire process of topic modelling is illustrated in Figure 3. Only the topics of the tweets of the latter period were modelled because the term discovery was aimed at discovering terms for a newly emerged topic, which in this case was COVID-related services at the airport. Prior to determining the number of topics, the data was processed. In this phase the tweets were run through a part-of-speech tagger and only nouns were selected. In addition, very low frequency terms were filtered out. After the preprocessing, the dimensionality of the feature space was further reduced using principal component analysis (PCA).

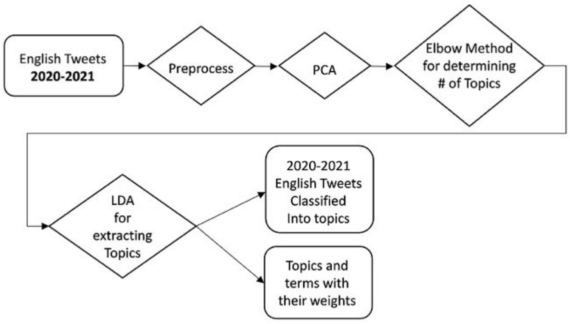

Figure 3: The topic modeling process using principal component analysis (PCA), the elbow method and the LDA method. As output, all tweets are categorized to the most probable topic. In addition, a list of terms and their weights is produced for each topic.

The process of discovering new COVID-related terms is illustrated in Figure 4. The input consists of the English tweets of the latter period under study and of a list of COVID terms. The idea is that a list of terms is given as a seed for the system and the system then extracts from the tweets terms that could belong to the same topic. The process of term extraction is as follows: first the COVID-related tweets are filtered from the entire body of tweets. Then they are preprocessed using the same methods as in the topic modeling that was described above (see Figure 2). After this each term and its frequency is calculated and a list of terms sorted according to term frequency (TF) is produced. This list is one output of the method. The other output is obtained when from the list of frequency-sorted terms those terms that occur in the previous period are filtered out. These terms are called COVID Terms in Figure 4.

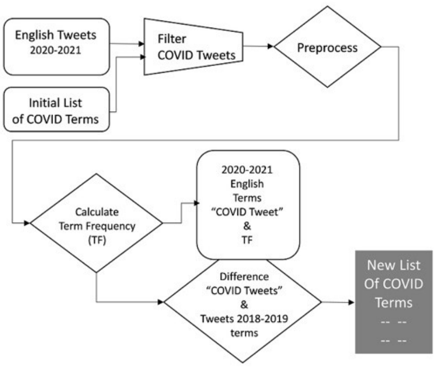

Figure 4: Discovery of new COVID terms from the tweets.

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The initial list of COVID terms used in this study is given in Table 3 below. As can be seen from the table, this list is very short and contains terms that an average native speaker of the language could produce without great effort. Thus, taking this method into use does not require an investment in terms of human resources, which shows that the proposed method has attained one of its goals, namely that of partly automating the process of finding new terms related to an emerging topic. However, there is one requirement that the creator of the initial list of terms should respect: The terms in the initial list should not be polysemous (i.e., words with more than one meaning) in the airport context. Rather, they should only bear a coronavirus-related meaning in the context of airport services.

4. Results

The sentiment analysis of the tweets supports results from previous studies where the overall sentiment concerning the airport services is slightly positive, see e.g., Martin-Domingo [4]. The results of the sentiment analysis may be observed in Table 1. The mean sentiment in the period 2018-2019 is 0.136 and in the period 2020-2021 it is slightly more positive with a mean value of 0.150. However, the mean sentiment value for the COVID-related tweets is lower: 0.095. The COVID-related tweets are those tweets that contain at least one initial COVID term listed in Table 3.

Table 1: The descriptive statistics for the sentiment scores of the three data sets.

Statistic	*2018 and 2019*	*2020 and 2021*	*COVID-related tweets*
Min	-0.800	-1.000	-0.667
Max	1.000	1.000	0.625
Mean	0.136	0.150	**0.095**
SD	0.170	0.181	0.134
Quartile 1	0.000	0.077	0.000
Quartile 3	0.250	0.250	0.167

The topic detection was applied to the tweets from 2020-2021. The number of topics found by the elbow method was three and they are the following: topic 1 is about miscellaneous topics such as spending time at the airport and greetings. Tweets mainly classified into topic 2 are about COVID-related services and issues. Topic 3 contains tweets about spending time at the airport, especially spending the night there. Table 2 lists some examples of the tweets in each topic. The score indicates the probability of the tweet belonging to the topic. After manual inspection of the most probable topics, it was discovered that each topic also contains tweets that are not related to the identified topics. The terms characterizing the topics are surprisingly generic and common to all topics. However, there are some topic specific terms, and the weights of the terms differ in the topics.

Table 2. Examples of tweets in each topic with the score indicating the probability for belonging to the topic.

Score	Topic	Example tweet
0.981	1	Can I get a pint at the bar in your airport
0.980	1	Happy New Year, thanks for sticking by us this year - You had a fairly tough year yourself but took the time to make us smile. Here's hoping we meet again very soon. Until then, stay safe my friend!
0.980	2	After the government 's update on the PCR tests here: https://t.co/giipldyjTH , are there any new restrictions on domestic travel within Canada?
0.980	2	Bruh are you guys not testing domestic passengers
0.990	3	Hello again! My flight arrives at 20:15 and my connecting one leaves at 12:05 the next day. Is terminal 5 open 24h and is it ok to spend the night there? Thank you!
0.990	3	Can people spend a night to the airport s hotel waiting for the connecting flight due the day after?

The new list of COVID terms discovered by the proposed method is included in Table 3. Terms not related to coronavirus or terms that are related to it only in some specific contexts (such as the terms arrival and center) have been filtered out from the above list. The accuracy of the system is 50% at 20 and 22% at 100, meaning that among the top 20 terms retrieved by the system, the proportion of coronavirus-related terms is 50%, whereas among the top 100 terms, their proportion is 22%.

Table 3: The initial list of COVID terms given as a seed to the system and the list of coronavirus related terms discovered by the proposed method.

Initial List of COVID terms	**New list of COVID terms**	
alfa variant	certificate	quarantine
British variant	check	result
corona	crowd	risk
COVID	distance	rule
delta variant	dog	safety
delta virus	fear	sanitizer
Indian variant	force	screening
mask	health	spread
omicron	lockdown	test
pandemics	measure	testing
physical distance	pandemic	vaccine
safe distance	pcr	virus
safety distance		
social distance		

5 Analysis

The study attempted to define and test a methodology for analyzing user-generated contents that allows to gain insight into the services in the airport collaborative network,

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especially into the sentiment of the passengers and the topics under discussion. The methodology for discovering new terms on an emerging topic was tested on COVID-19 related tweets, but it was designed to be generic enough to enable the discovery of terms and contents related to other emergent topics, such as Brexit consequences or lack of personnel at the airports. Furthermore, the methodology could be applied also to other collaborative networks consisting of various services with abundant user-generated contents, such as a shopping mall or a railway station.

The study used lexicon-based sentiment analysis. The results support previous research by showing that the overall sentiment of the tweets in the airports is slightly positive. When studying the sentiment related to COVID-19 topics, a drop in the sentiment was found. Previous research on sentiment analysis of user-generated content shows a drop in sentiment concerning airport service quality during the COVID period [29]. However, research on the sentiment perceived in relation to services related to COVID-19 (such as control of vaccination certificates or instructions for the usage of masks), is scarce. Thus, the present research results provide new knowledge on this as it conducted sentiment analysis on COVID-19 related tweets where each tweet was somehow related to both COVID-19 and an ecosystem of airport services.

The LDA method was used to discover topics in the tweets. This was successful and three topics were discovered. The terms related to the topics did not very well describe them. Therefore, an inspection of the tweets classified into each topic was used to describe the topics discovered. The terms describing the topics found by the LDA method were the same to a great extent, only some terms were different, and the weights were different. This is probably due to the small number of coronavirus-related tweets and especially due to the small number of terms in the tweets. The small number of terms is partly due to the methodology used. The method used did a considerable dimensionality reduction for the terms as first PCA was performed. After that, in the preprocessing phase, part-of-speech tagging was conducted and all other words except nouns were filtered out. At the end, words with a low term frequency were filtered out. All these three phases contributed to the small number of terms that were passed on first to the elbow method and subsequently to the LDA method.

When evaluating the results of the term discovery method that came up with new COVID-related terms, it was noticed that it is not at all easy to define the borderline between a COVID term and a non-COVID term. The context of use is the ultimate source that tells whether a term in question is a COVID-related term or not. However, in the classification of documents or in libraries, topical terms are commonly used without any context. These terms are used to describe the contents of documents or customer reviews and users use them for search.

In this study, when determining whether a word is a COVID term or not, human expertise in the field of airport service quality and the context of the word were used. The task was not at all easy. Thus, it is probable that it is not at all easy for an automated methodology, either. Words like dog, screening and result were classified as COVID terms even though they are very often also used in the sense of a non-COVID term. However, the dogs that are trained to detect COVID, the testing or screening of COVID certificates upon arrival and the result of a COVID test are common contexts where these words may be regarded as COVID-related terms.

One limitation of the study is that it used lexicon-based sentiment analysis and word-based representations for topic discovery. However, Twitter messages also contain non-textual and rich contents as well as metadata that could be very important to the analysis [32] . Examples of such non-textual or rich contents are emojis, images, and hyperlinks. A future study could process the rich contents in the tweets along with the textual contents and probably reach even more accurate results than the present study. Another limitation of the present study is that it did not leverage the network structure of the Twitter data. It is regarded an important source of additional information. It consists of retweets, likes, mentions of tweets and of twitter accounts, among others. There are methods for discovering communities of Twitter users that are centered around a topic, such as airports [33]. It might be worth investigating if leveraging this network structure would bring additional information for the process of co-creation and help in identifying novel improvement areas in airport services. A third limitation of the study is that it used representations based only on one word. A future study using collocations consisting of several words may bring more insight into the topic.

6 Conclusions

This paper described an attempt to define and test a methodology for analyzing user-generated contents to gain insight into the services provided by an ecosystem of actors forming a collaborative network, from the topics and sentiments mined from the user-generated content. The methodology was tested on COVID-19 related tweets concerning 100 airports.

Twitter data concerning the 100 most followed airports from 2018 and 2022 was used as the data set that was mined. As a result, it was observed that the sentiment of the tweets varied across topics. A difference in mean sentiment was also found when comparing COVID-19 services related tweets (lower sentiment), with the overall sentiment. The study, using automated methods, generated a novel list of COVID-related terms to measure service quality provided by the airport collaborative network. However, the results of the LDA method were a bit surprising as the number of discovered topics was smaller than expected and the terms describing the topics were not as topical as expected. The reason for this was probably the small amount of data and the powerful dimensionality reduction in the preprocessing phase. In a future study, dimensionality reduction before the actual topic modelling phase could be modified to keep more dimensions.

The study contributes to the user-generated data mining and text analytics debate where social media data is leveraged to enhance managerial decision making, for improving airport services and data engineering methods. The study illustrated how airports may leverage the richness of data that is now days available to them as they have become a part of a data-rich collaborative network due to digitalization. The study illustrates how airport collaborative networks can profit from the richness of data using a co-creation process, where passenger generated content is leveraged to identify possible service improvement areas.

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