Sentiment analysis resource of Libyan dialect for Libyan Airlines

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ABSTRACT

Arabic lacks extensive corpora for natural language processing (NLP) when compared to other languages, namely in the Libyan dialect (LD). Therefore, this study proposes the first corpus of Arabic sentiment analysis (ASA) of the Libyan Dialect for the Airline Industry (ASALDA). It comprises 9,350 comments and tweets, annotating them manually depending on text polarity into three labels: positive, negative, and neutral, and utilized aspect-based sentiment analysis (SA) to annotate opinions regarding fifteen aspects. Also constructs a simple sentiment lexicon of the LD. The solution is based on the idea that the corpus and lexicon can be helpful models to improve classification for the LD. The approach has notable merits, namely creating a corpus and sentiment lexicon for the LD from comments and tweets of airline companies. A comprehensive verification using a statistical technique called the chi-square test is carried out with the corpus to determine if two aspects are related to one another. Based on the statistical work, we found that airlines should focus on improving their services in aspects where they are performing poorly, such as late flights, customer service, or price. The corpus and lexicon that we proposed can be utilized to perform many opinion mining and SA experimentations using machine learning and deep learning.

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1. INTRODUCTION

The variety of Arabic language which is used in informal situations and day-to-day interactions is labelled dialectal Arabic (Aammiyya), as opposed to the standard variety which is used in formal settings. However, dialects vary from nation to nation and between regions in the same nation. Some Arabic dialects are an amalgam of regionally spoken, dialectal, Arabic and modern standard Arabic (MSA). Levantine Arabic, Gulf Arabic, Maghrebi Arabic (spoken widely in Libya, Tunisia, Algeria, Mauritania, and, Morocco), and Egyptian Arabic are the four primary dialectal families of Arabic [1]. An estimated six million people speak the dialect in Libya, with a small portion also speaking it in neighbor countries [2]. The Libyan dialect (LD) is now one of the languages reviving researchers' attention and is being used to create a dataset for several natural language processing (NLP) applications [3].

Sentiment analysis (SA) is a NLP task that is used to identify opinions as neutral, negative, and positive. The academic world is quite interested in a number of SA research's either for MSA language or for Arabic dialects such as Tunisian, Moroccan, and Saudi [4].

Arab Internet users communicate with others through social media platforms like Facebook and Twitter in their own dialect. Airlines companies plays a crucial role in modern transportation because they are under increasing pressure to provide excellent services which can meet the demands and expectations of their customers. So, researchers interested in airline companies may effectively utilize these platforms as significant data sources to build their corpus or dataset which may be used later to analyze passenger sentiments about offered services. Singh and Upreti [5] found that airlines companies use extensive customer feedback, analyzing sentiments of airlines is necessary to minimize problems. In addition to work of Alhammi and Alfared [3], Singh and Upreti [5] attempted to create a sentence-level training dataset for the LD.

Despite the numerous works carried out on the SA, no previous study has thoroughly investigated sentiments on social media related to Libyan Airline companies. The Libyan Airline industry continues to expand. The main interest of this study lies in collecting comments and tweets on social media expressed towards Libyan Airline companies and classifying them and creating a sentiment lexicon. This work is very important to both researchers in LD and airline companies to understand customer sentiment towards the various airlines operating in the state of Libya. This research makes a significant contribution to this field of study by designing the first corpus of ASALDA for the Libyan Airline industry as well as a sentiment lexicon for LD. The focus of SA is placed on the LD, which is a member of the Maghrebi Arabic family, and the online means to garner information are Facebook and Twitter.

The remainder of the research is arranged as follows. Some studies on SA are highlighted in section 2. The proposed method contains a corpus and sentiment lexicon in section 3. The last portion concludes with a presentation of the conclusion and future work.

2. RELATED WORK

The task of SA is gaining considerable interest in the field of Arabic NLP (ANLP). However, due to the lack of a publicly accessible dataset for Arabic, few studies have attempted to apply SA to this language [6]. Arabic lacks extensive corpora for NLP compared to other languages [7], [8]. In order to overcome this lack, some researchers have relied on translations from one language to another to build their corpus [9]. Table 1 shows details about some of the Arabic corpora.

Table 1. Some Arabic corpora

Corpora	Size	Reference
COVID-19 pandemic in Saudi Arabia	157,214 tweets	Alqarni and Rahman [10]
Twitter Benchmark Dataset for Arabic SA	151,000 sentences	Gamal *et al.* [8]
Corpus for SA	4,700 tweets	Assiri *et al.* [7]
Sentiment corpus for Saudi dialect	4,000 tweets	Alqarafi *et al.* [11]
AraSenti-Tweet Corpus of Arabic SA	17,573 tweets	Al-Twairesh *et al.* [12]
Health dataset	2026 tweets	Alayba *et al.* [13]
Arabic sentiment tweets dataset (ASTD)	10,000 Egyptian dialect	Nabil *et al.* [14]
TAGREED	3,015 tweets	Abdul-Mageed *et al.* [15]
MARSA Gulf area	61,353 tweets	Alowisheq *et al.* [16]

The first Telecom GSC for dialectal Arabic (DA) for Arabic sentiment analysis (ASA) was developed, cleaned, pre-processed, and annotated by Almuqren, and Cristea [17]. This resource, called AraCust, comprises tweets in the Saudi dialect that have been manually labelled and annotated for SA using a self-collected Arabic tweets dataset.

Fsih *et al.* [18] built two SA resources: sentiment lexicon and annotated corpus. They exploited these resources in developing SA model based on user-generated comments on social media about television shows in Tunisia. Abdi and Ramaha, [19] created sentiment dataset for Somali language which was annotated through crowdsourcing. They offered an approach to efficiently extract sentiment by combining feature engineering with lexicon-based method. Benali *et al.* [20] provide linguistic resources for the automated processing of the Algerian dialect. It utilized grammar rules extracted from the corpus to do segmentation of written texts and by the translation of few rules from different dialects.

AlMasaud and Al-Baity [21] built AraMA which is the first and the largest Arabic multi-aspect corpus. About 10,750 Google Maps reviews of restaurants in Riyadh, Saudi Arabia are included in AraMA. Reviews are labeled according to four polarities (positive, negative, neutral, and conflict) in addition to four aspects (food, environment, service, and price).

In addition to SA dataset, sentiment lexicon is considered to be an important resource for the majority of SA algorithms [22], [23]. To determine sentence’s polarity, there are three basic approaches: lexicon-based approach, machine learning-based approach and hybrid approach [24]. Lexicon-based techniques use sentiment lexicons which can be generated automatically or manually using seed words to increase the number of possible phrases [25]. These lexicons can be divided into general-purpose and domain-specific categories. The Arabic sentiment-lexicon described by Al-Moslmi *et al.* [24], it consists of 3880 positive and negative synsets, each of which is annotated with its part of speech, inflected forms, dialect synsets, and polarity score.

A short seed list of negative and positive terms was used to build an Arabic lexicon (ASL), which was presented by [26], the polarity ratings were assigned to a total of 2,000 words (800 positives, 600 negatives, and 600 neutrals words) using a semi-supervised approach. In order to create the Arabic SentiWordNet (ArSenL), Badaro *et al.* [27] combined the English SentiWordNet (ESWN), the standard Arabic morphological analyzer (SAMA), and an Arabic WordNet, the generated lexicon has a total of 28,780 lemmas after manual correction and 28,812 lemmas for automatic processing for ArSenL-Union. Bouamor *et al.* [28] provide two resources created as a result of the multi Arabic dialect applications and resources (MADAR) project. The first is a significant parallel corpus of travel-related Arabic in 25 city dialects. The second vocabulary consists of 1,045 concepts, each of which is represented by an average of 45 words from 25 different places.

Despite the Middle East aviation market's recovery advancing throughout 2022, it is anticipated to take off over the next ten years as the region's proportion of the world fleet is forecast to rise. The Middle East continues to be one of the world's fastest-growing aviation markets, Oliver Wyman observed in its "Global Fleet and MRO Market Forecast 2023-2033," with the region's fleet expected to increase by 5.1% annually over the following ten years. The survey also stated that the Middle East's fleet share will increase over the next ten years, rising from 4.9% in 2023 to 6% in 2033 [29]. Facebook and Instagram are the two most significant social media platforms that consumers consult when selecting an airline ticket since they facilitate easy access to airlines [30].

Recently, there’s an interest in analyzing sentiments expressed towards Airlines companies. Recent findings from a study by [31] support the significant impact of in-flight food and beverage quality on passengers' perceptions of price reasonableness, airline image, and overall satisfaction, influencing their decision to fly again. Baker [32] compared customer satisfaction and service quality dimensions to examine the correlations between service quality aspects and passengers' satisfaction with airline services for the top 14 U.S. Airlines. Rustam *et al.* [33] utilized a Kaggle dataset containing tweets from six US Airlines, which consisted of 14,640 records. Records were categorized as positive, negative, or neutral based on the degree of sentiment polarity. Sulu *et al.* [34] identify the main themes that surfaced from online evaluations written by airline passengers during the COVID-19 pandemic. It also makes an effort to identify which of these themes is associated with greater and lower levels of passenger satisfaction. Arul and Tahir [35] make use of a model of social media attributes that is composed of five aspects to know the impact of social media on customer relationship management programs within the context of airline passengers.

However, few studies are interested in SA for LD. Alhammi and Alfard [2] present a corpus for LD, consisting of 5,000 statements written by Libyan Twitter users. The corpus undergoes manual classification into fifteen categories, and the statistical analysis of the corpus data reveals a significant variation in the number of tweets across categories, with the film’s category having the lowest number of tweets. Alhammi and Haddar [36] conduct their research using 5,000 phrases or tweets from a publicly accessible Twitter corpus written in the dialect of Libya. About 108 adjectives were kept in a dictionary for adjectives as a consequence of manually gathering adjectives and adverbs from the research data set to generate sentiment dictionaries or lexicons. Miskeen *et al.* [37] conducted a study to evaluate the service quality of local Airline companies in Libya. They utilized importance satisfaction analysis (ISA) to assess customer satisfaction and identify areas for improvement. A questionnaire was personally administered to a sample of 312 domestic air travelers within Libya, providing valuable insights for enhancing service quality and improving customer satisfaction in the airline industry. Ehbara and Shukor [38] examined the relationship between consumer trust in service quality parameters and the Libyan Airline industry. The study highlights the security difficulties faced by passengers flying on Libyan Airlines due to the rise in traffic accidents, congestion, and pollution. Thus, there is a lack of resources for SA for the LD in general and specifically towards Libyan Airlines.

3. THE PROPOSED METHOD

This section describes the proposed method for SA related to the LD, which comprises three main steps, namely, (A) Corpus description, (B) statistical study of Corpus, (C) sentiment lexicon, and (D) word cloud text visualization.

3.1. ASALDA corpus

This study has investigated sentiments of passengers towards Libyan Airline companies. The participants were customers of the Libyan aviation sector. The study did not entail any contact with the participants. In order to improve Libyan Airlines' services and enhance customer loyalty so they should understand their customers' opinions and satisfaction levels. The development of the proposed corpus is based on hypothesis that customer sentiment towards Libyan Airlines is influenced by combination of functional and emotional factors. Functional factors refer to aspects of airline service that are related to its core function such as on-time performance and baggage handling while emotional factors refer to aspects that are related to customer's emotional experience such as comfort and customer service.

3.2. Corpus description

The data were collected from social media platforms such as Facebook and Twitter, comprising about 100K comments and tweets posted by customers from 2009 to 2023 concerning Libyan Airlines: Afriqiyah_Airways, Air-Libya, AlRahela, Buraq_Airline, Ghadames_Air, Libya_Wings, Libyan_Airlines. Some comments include reviews related to many airline companies at the same time. We selected 9,350 comments and tweets that were written in the LD. Figure 1 shows the number of comments and tweets that belong to each airline company.

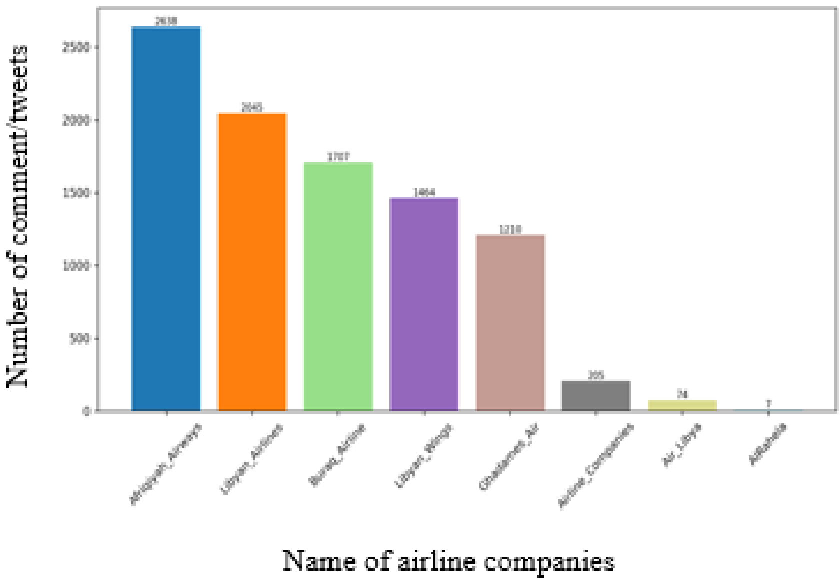

Figure 1. Number of comments/tweets for each airline company

In order to create our corpus, we have used the Face pager tool [39] to fetch Libyan comments from Facebook based on the IDs of the airline companies' pages. In addition, Python script [40] has been used to fetch Libyan tweets from Twitter based on specific search keys. To reduce noise in the data, the data have been cleaned and pre-processed using Python script. As recommended by [41], [42], comments and tweets have been sanitized by deleting superfluous elements like non-Arabic words, characters (like %, +, and $), punctuation (like ", ", ".", and ";"), numbers, and user mentions (@user).

Additionally, data were normalized, which involves the unification of specific types of Arabic letters that have different shapes, as in Al-Twairesh *et al.* [12]. So, emoticons have been moved from comments into a new attribute since previous studies indicated that classifiers mistook the parentheses in the quote for the ones in the emoticon [41]. Also, [42] demonstrated that using emoticons in classification lowered the classifier's performance when dealing with Arabic tweets. Comments and tweets were manually labeled as positive, negative, or neutral for sentiment based on sentence level and also labeled on an aspect-based level. Since manual annotation is carried out by humans, it is more accurate and trustworthy, in spite of the fact that can be a time-consuming process.

We named our corpus ASALDA, which stands for ASA for the LD of the airline companies. Table 2 illustrates the number of comments/tweets and the number of words that belong to positive, negative, and neutral polarity. In addition, we annotated opinions on an aspect level. We proposed a set of fifteen aspects related to the airline domain: customer service, flight delay, flight cancellation, lost luggage, damaged luggage, food, flight, pricing, cleanliness, flight booking, general, flag, airport, plane, and crew. Table 3 and Figure 2 show the number of negative, neutral, and positive sentiments related to each aspect for airline companies, highlighting the different levels of customer engagement and interest.

Table 2. Number of comment/tweet for sentiments and words for each airline

	Positive	Negative	Neutral
No of comments and tweets	2,044	4,187	3,119
No of words	23,095	71,352	26,369

Table 3. Number of negative, neutral and positive sentiments for each aspect

Aspects	Negative	Neutral	Positive	Total
Late_flight	1,210	36	414	1,660
Cancelled_flight	354	6	0	360
Lost_luggage	128	4	1	133
Customer_service_issue	632	1,853	228	2,713
Flight_booking	61	28	12	101
Damaged_luggage	8	0	0	8
Food	159	35	97	291
flight	94	2	73	169
Price	421	697	68	1,186
Clean	27	0	6	33
General	1,056	374	1,006	2,436
Flag	19	26	35	80
Airport	46	6	6	58
Plane	383	43	25	451
Crew	116	18	284	418

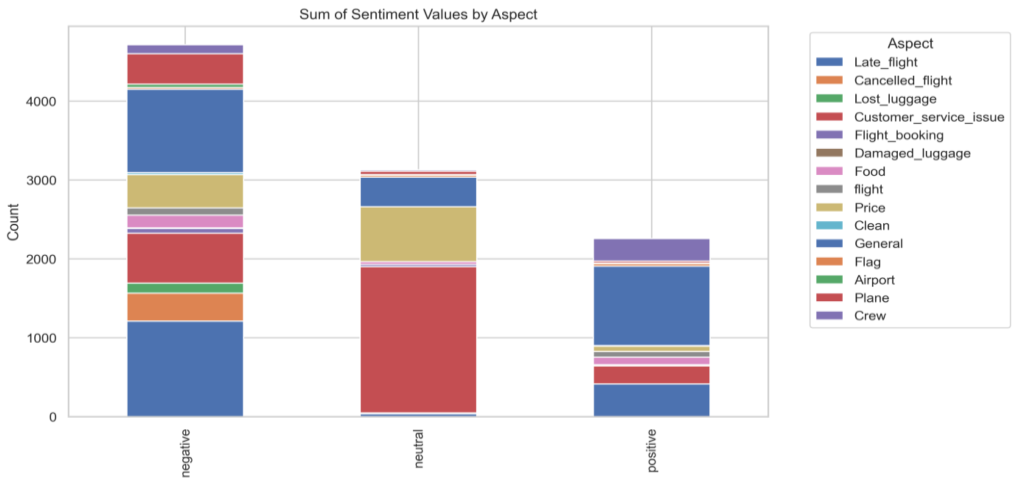

Figure 2. Number of positive, negative, and neutral sentiments for each aspect

To ensure consistency and dependability during the manual annotation of the corpus, the annotators performed the test-retest reliability, which compared the labels assigned to the same comment/tweet at two separate times to assess the consistency of the SA. Figure 3 presents an excerpt of data from ASALDA without mentioning the name of the airline company. The aspect column lists the name of the aspect; the word count column shows the number of words in the comment or tweet; the emoji column describes the emoji icon; the polarity column contains positive, negative, or neutral sentiment; and the comment column presents the comment or tweet text.

Preliminary experiments were performed with balanced dataset that contains 2,000 positive, 2,000 negative, and 2,000 neutral comments by using some machine learning algorithms [43]. The ASALDA corpus was stored in two different shapes. First, the data were written in a standard XML file format as shown in Figure 4, and the second, saved in its entirety into an excel file, as shown in Figure 3.

Comment	Polarity	emoji	word_count	Aspects
ما شاء الله معاملة روعة وبشاشة ومواعيد ولا اروع منكم تجربة حلوه معاكم موفقين	positive	💜	14	Late_flight
الخطوط الجويه التشحيطيه	negative	❤️	3	Late_flight
وبالله عطونا نبده عن مواعيدكم	neutral	🤮	5	Late_flight
مش موفقين ان شاء الله الناس تحجز و انتم الغوا الرحله بعدها و ماتقولوش امتى قعدت	negative	🤬	16	Cancelled_flight
رحلة يوم الأربعاء بنغازي اسطنبول ملغيه لمده شهر ما عدا يوم الاثنين و الجمعه ع متن الخطوط	neutral	⬜👍	19	Cancelled_flight
موفقين دائما ان شاء الله وبانتظار خط مصر في شهر او قبل ياريت	positive	😍	13	Flight_booking
م عمري صادفت وجبه ديما اسافر ف رمضان ونكون صايمه	neutral	💔😂😭	10	Food
أحلى خطوط أسعار رخيصة معاملة راقية مواعيد منظمة نتمنى منكم الأستمرار موفقين	positive	🥰🤗🤔	12	Price
به رخصو اسعاركم شوية	negative	😔	4	Price

Figure 3. An excerpt of corpus data of ASALDA’s structure in Excel file

```xml
<?xml version='1.0' encoding='utf-8'?>
<Airlines>
<Airlines name="Afriqiyah_Airways">
<Comment id="34"><comment_text>وبالله عطونا نبدة عن مواعيدكم </comment_text>
<Polarity>neutral</Polarity><emoji>🤮</emoji><word_count>5</word_count>
<Aspects>Late_flight</Aspects>
</Comment>
```

Figure 4. Corpus ASALDA’s structure in XML file

3.3. Statistical study

The statistical study illustrates that customer sentiment is significantly different between aspects. As presented in Table 3, "customer service" is the most commonly reviewed aspect with a total of 2,713 sentiments; this describes a significant area of concern for customers. "General" is the second most mentioned aspect, with a total of 2,436 instances, for 1,006 positive and 1,056 negative instances. The third most mentioned aspect is "Late_flight" with 1,660 mentions overall. This aspect has the highest proportion of negative sentiment with 1,210 mentions, which is over 72% of the total mentions for this aspect. This indicates the importance of on-time flights for airline customers. "Cancelled_flight" holds 354 negative mentions, which is nearly 98% of total mentions for this aspect. This indicates a high level of dissatisfaction due to flight cancellations. "Crew" is the only aspect that has a higher proportion of positive mentions at 284 out of 418 total at a percentage of 67.94%. This indicates that customers are generally satisfied with the airline's crew. As shown in Table 3, we remark that "Late_flight," "Cancelled_flight," and "Customer service" aspects have a higher number of negative mentions at 128, 354, and 632, respectively.

The number of comments/tweets about Lost_luggage and Flight_booking aspects are not big, but it has a higher negative opinion than other positive and neutral ones, so the airline company must consider that. Damaged aspect only has 8 negative comment/tweets from 4,178 negative. This means only 0.191% of the negative feedback is related to the "damaged aspect." It is an extremely rare issue in Airline company. The "Food" aspect has a dominantly negative sentiment 54.6% from 291, indicating it is a key area of concern. While there is some positive feedback 33.3%, the high proportion of negative comments suggests that improvements are needed. So, it should focus on improving the quality of food. Similar to "Food" aspect, the majority of feedback about the "Flight" aspect is negative 55.6%, indicating users are more dissatisfied than satisfied with this aspect; on the other hand, about 43.2% of users still have a good experience with "Flight" aspect. "Price" aspect has a dominantly neutral sentiment 58.8%, indicating most users do not have any strong sentiments about it. However, some of users 35.5% are dissatisfied with price, while very few 5.7% are satisfied. The high percentage of negative feedback related to "Clean" aspect based on the total of comments, about 81.8%, suggests this aspect is a critical problem area that requires immediate attention. This could indicate issues with overall cleanliness standards. "Flag" aspect is generally well-received with 43.75% positive feedback. This could indicate that users appreciate whatever "flag" represents like branding or national identity. However, there is still notable amount of neutral 32.5% and negative 23.75% feedback. The majority of feedback about "Airport" aspect is negative 79.3%. So, this could indicate some issues with airport facilities or services. Both neutral and positive feedback make up 10.3% each, suggesting that very few users are either satisfied or indifferent about "Airport" aspect. The overwhelming majority of feedback about "Plane" aspect is 383 negative comments/tweets about 84.9%; this may indicate that users are highly dissatisfied with uncomfortable seating, lack of legroom, or old planes.

These suggest that airlines should focus on these aspects to satisfy their customers. In order to examine relationships between 15 aspects that are aforementioned and customers' sentiments in Libyan Airlines, we have performed a chi-square analysis as seen in Figure 5. Tallarida and Murray [44] proposed a statistical technique called the chi-square test, which allows researchers to determine if two categorical variables are related to one another. Franke *et al.* [45] have explained the applications and interpretations of the family of Pearson's chi-square tests, with a particular emphasis on tests for independence and homogeneity of variance (identical distributions). A chi-square test was utilized to investigate significant differences in sentiment across different aspects among airlines. A correlation matrix is presented in Figure 5, where each row/column represents an aspect, and values indicate the strength of correlation between these aspects.

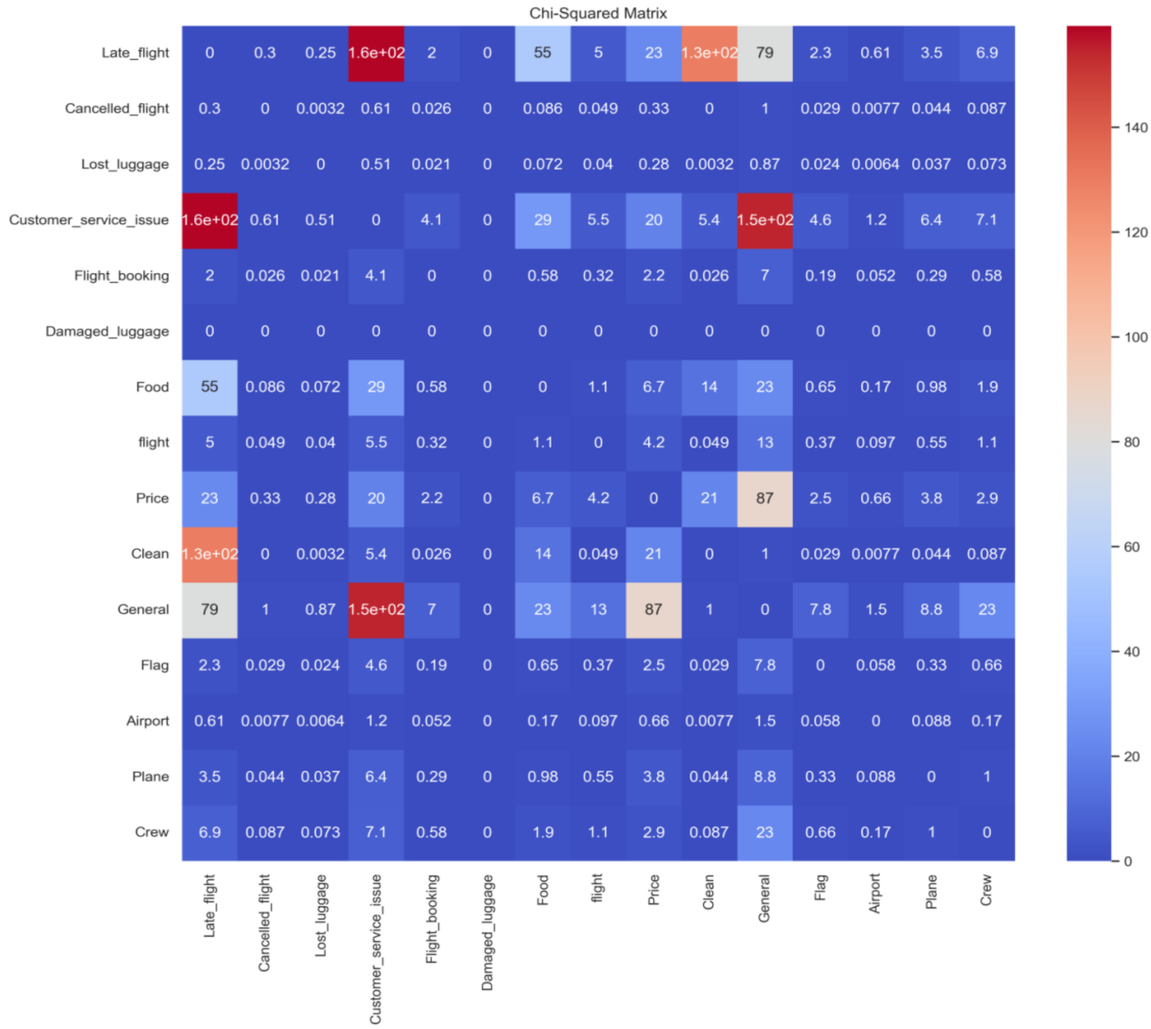

Figure 5. Chi-square heatmap shows the relationships between the 15 aspects

"Late_flight" is highly correlated with "Customer_service" (160.0) and with "Clean" (130.0). Also "Customer_service_issue" is highly correlated with "General" (152.0) and "Price" (152.0). In other hand, "Damaged_luggage" has a weak correlation of 0.0 with all other aspects this indicating no correlation. Also "Flight_booking" has relatively low correlations with most other aspects except for "Customer_service_issue" (4.1) and "Price" (7.0). Also, data suggest that factors as late flights, customer service, and cleanliness are strongly correlated with each other and with overall customer satisfaction (represented by general aspect). Additionally, food quality seems to be an important factor in customer satisfaction. Lack of correlation for damaged luggage could indicates that it is relatively rare occurrence or handled effectively by airline.

3.4. ASALDA sentiment lexicon

We have created a sentiment lexicon by extracting words and phrases from the annotated ASALDA corpus. The sentiment lexicon has three columns: positive, negative, and neutral. The total of words/phrases is 19,500 from all columns. Words/phrases were reviewed and classified manually. The lexicon contains 2,000 positive words/phrases such as مليح *malih* (nice), and بوركت *burkit* (blessed) in the positive column, 5,500 negative words/phrases such as بهدله *bhdalah* (messed up), and شحورونا *shihuruna* (made a fool of us) in the negative column, and 12,000 neutral words/phrases such as مواعيد *mawaeid* (appointments), and اخدمو *akhdmu* (serve) in the neutral column. The sentiment lexicon was stored in an Excel file. This lexicon will be useful in classifying sentiments for LD using machine learning and deep learning based methods.

3.5. Word cloud

Word cloud became a popular and remarkable way for text visualization. Word cloud have been shown to be an efficient tool for solving text analysis tasks and evaluating the results in qualitative user research [46], they are employed in a variety of settings to give an overview of the terms that occur with the highest frequency. Word cloud has been proposed as the new reading training tool for English instructors since it serves as a rapid visualization mechanism for evaluating and investigating English literature [47]. In the area of computer science, it tends to offer a dynamically interactive word cloud visualization system based on the D3 and JQuery techniques.

Word cloud analysis was conducted to identify the most frequently used positive and negative words in the tweets and comments related to the Libyan Airline companies. We extracted all words from ASALDA corpus based on positive comments and negative comments, and then we utilized Word Cloud to analyze them. The word cloud for positive words indicated that customers frequently used words such as موفقين *muafiqin* (Good luck) to describe their sentiments, as shown in Figure 6.

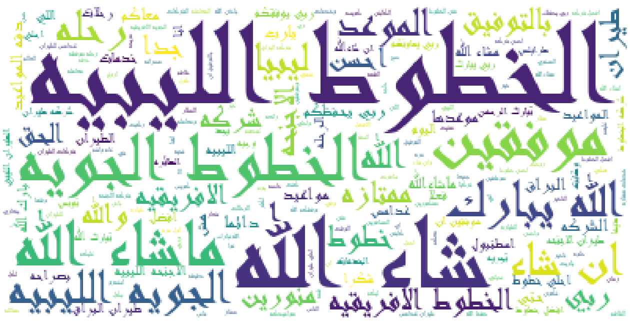

Figure 6. Positive words

4. DISCUSSION

Statistical study shows that customer service issues are strongly associated with multiple aspects like late flights and price, improving customer service could have a cascading positive effect on overall satisfaction, and consider revisiting pricing strategies. While food complaints are not the most dominant. Enhancing food quality could help reduce overall dissatisfaction. Damaged luggage appears to be an isolated issue. While it may not be a major driver of dissatisfaction, it should still be addressed to prevent negative experiences. Han *et al.* [31] shows how the quality of the food and drinks served in flight affects customers' opinions of overall contentment and reasonableness of pricing, all of which affect whether or not they choose to travel again. According to research by Baker [32], low-cost airlines often provide better service than major legacy airlines. There were clear implications for infrastructure, market share, customer service, and operational expenses.

The chi-square test confirms there is a relationship between some aspects, so they should improve together these aspects. In contrast, the chi-square test is displayed to be a non-relationship between some aspects. Interestingly, the correlation between Damaged_luggage and any aspects is not as expected; there is not any relationship between them.

The results provided by this study have evident and important implications for airlines seeking to improve customer satisfaction and loyalty. These suggest that airlines should focus on improving their services in aspects where they are performing poorly, such as late flights, customer service, or price. By identifying aspects that influence customer sentiment, airlines could make improvements to their services to enhance overall customer satisfaction.

5. CONCLUSION AND FUTURE WORK

The objective of the current study as a contribution was to present two resources for SA for the LD: the ASALDA corpus and a sentiment lexicon. The ASALDA corpus contains customer comments and tweets towards airline companies. These comments were annotated according to polarity level and aspect level. The ASALDA corpus may be utilized to perform many opinion mining and SA experimentations using deep learning algorithms. Words and phrases in the sentiment lexicon were classified into three polarities.

This statistical study was undertaken to know the sentiments of passengers about airline services. The investigation has concluded that there is important relationship between some aspects. The observations from this study suggest that generally the research will help airlines themselves to improve customer satisfaction and service quality. This research is envisaged to serve as a base for future studies. We consider that we will undertake further research's in the following areas: focus more on extending the corpus using data augmentation techniques and explore more techniques related to SA.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This study has investigated passenger sentiments toward Libyan Airline companies. The participants were customers of the Libyan aviation sector. The study did not entail any contact with the participants. All data that we used are available online.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Hassan Ebrahem], upon reasonable request.

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