Measuring the correlation of service expectations of travelers in selected international KSA airports through Bilingual Sentiment and Clustering Analysis

Eng. Haya Altajel, and Dr. Faisal Alotaibi
Industrial Engineering Department
Alfaisal University
Riyadh, Saudi Arabia
hnaltajel@alfaisal.edu, fotaibi@alfaisal.edu

Abstract

This study analyzes customer reviews by applying Sentiment Analysis to test the similarity of expectations in airport experiences shared by domestic and international travelers in the 3 top busiest airports in Saudi Arabia and measure the correlation extent of their expectations in each airport. The study's methodology was by first collecting customers' verbatim comments in English and Arabic on the three major airports in Saudi Arabia, which are King Khalid Int. The airport in Riyadh, King Abdulaziz Int Airport in Jeddah, and King Fahad Int Airport in Dammam. The existing data is extracted from Skytrax, a prominent airline and airport reviewing website, and Twitter, the #1 social media platform used in Saudi Arabia. Second, preprocess the data through data cleaning for analysis preparation. Third, run the customers' verbatim comments database through Sentiment Analysis to identify the favorable and unfavorable services provided by the airports. Finally, stratify the data into clusters based on the outputs of the analysis. The expected outcome of applying SA is to essentially rank the customer's favorable and unfavorable services based on their verbatim feedback on the website domestic and international travelers.

Keywords
Opinion Mining, Cluster classification, Social Media Text Analysis, and Customer Reviews.

1. Introduction
Customers today use a wide range of communication channels to provide feedback on services and products offered by companies. These include social media pages, customer satisfaction surveys, customer emails, telephone calls, text messages, product reviews, and CRM (Customer Relationship Management) platforms. Due to the sheer magnitude of the data collected from these platforms, it has become necessary for experts to develop new efficient ways of analyzing the data (Fontanella, C., 2020).

In Saudi Arabia, Twitter is the most used social media data source, followed by Facebook and Instagram. Recent researchers that have also used Twitter as a source of data include (Yuliyanti & Sukoco, 2017), (Martin-Domingo et al., 2019), (Mansour, 2018), (Mahtab et al. 2018), and (Vishal & Uma, 2018). These studies mainly used machine learning tools and applications in English, such as RapidMiner, SVM, Python, and R. In general, the studies report a high success rate in classifying user sentiments.

Most of the research on Opinion Mining is tailored for the English language, and research on Arabic mining reviews is growing at a prolonged rate. When applying Sentiment Analysis on customer feedback on airport reviews in Saudi Arabia, there is no doubt that providing services to customers requires distinguished levels of service quality in order to achieve high satisfaction rates, encourage airlines and airports to optimize their operations, and enhance the reputation of Saudi Arabian airlines and airports thus supporting the development of the Tourism and National Heritage Sectors which is the 8th theme of the Kingdom's 2030 vision (*Vision 2030 | The Embassy of The Kingdom of Saudi Arabia*, 2016).

Over the past two years, Saudi Arabia opened its gateways to tourists from all around the world for the first time in its history as part of the Vision 2030 plan. Therefore, a necessity arises to examine the customer expectations in airport experiences and determine if Saudi airports may need to optimize the current services provided or introduce new dimensions of services to better fit both national and international customers' needs. Hence, the problem statement is to determine if Saudi airports may need to adjust the current services provided or introduce new dimensions of services to fit customers' needs.

1.1 Objectives

In this study, the research objectives can be regarded as follows:

1. Shed light on customers' unmonitored opinions on services provided.
2. Reduce the gap between customer expectations and the organization's recognition of the level of service quality.
3. By investigating the reviews from Voice of Customer, the study will recommend new dimensions (if any) of services to accommodate its travelers better.

2. Literature Review

One of the earliest implementations of Natural Language Processing (NLP) techniques in the analysis of text data was performed in a study by (Turney, 2001) and (Pang et al., 2002). They were among the first researchers to objectively classify user-generated opinions into two primary forms: positive and negative. In the study by (Turney, 2001), a simple unsupervised learning algorithm to analyze reviews was used. The algorithm gave a thumbs up for recommended reviews and a thumbs down for negative reviews. Both researchers use a PMI-IR (Pointwise Mutual Information (PMI) and Information Retrieval (IR)) algorithm that estimates the similarity of words and phrases used. The algorithm's accuracy was reported to be around 84% and 64% for two different types of reviews.

2.1 Sentiment Analysis Application Areas

Today, Sentiment analysis is applied in many industries, especially those driven by customer feedback. Sentiment analysis in the industry is primarily applied in customer feedback analysis. For instance, Tiwari et al. (2019) research implemented sentiment analysis for services offered by airlines. The analysis was based on a Twitter dataset. Association rule mining and BIRCH clustering were used. BIRCH clustering identified a positive and negative correlation between certain words and provided positive or negative customer feedback. Khan and Urolagin (2018) also implemented a similar dataset and research methodology, who reported a classification accuracy of 99.05%. Numerous researchers have used data generated from internal airline departments to assess customers' underlying sentiments and opinions. In a study by Mohan and Venu (2015), the researchers apply sentiment analysis techniques to data obtained from an airline's online forum. The researchers used Linear Support Vector and Naïve Bayes algorithms. A total of 2,172 reviews were analyzed. The analysis result was visualized, and a high level of accuracy (86%) was reported.

2.2 Arabic Sentiment Analysis and its challenges

Most researchers that have performed sentiment analysis for Arabic texts report several challenges. According to (Alahmary et al., 2019), sentiment analysis of Arabic texts has difficulties compared to other languages like English. Most of these difficulties are due to the complex rules surrounding Arabic texts and the Arabic language. For instance, apart from the widely used and standard Modern Standard Arabic (MSA), several other Arabic dialects vary from one community to another, such as Egyptian, Jordanian, Iraqi, etc., and the local dialects in each country. Local Saudi Arabian dialects include but are not limited to Najdi, Hijazi, Beduin Hijazi, Qasimi, Janobi, Haili, and Hadrami (Wikipedia, 2021). An example of word meaning variations based on dialects is illustrated in Table 1. Because of these differences, words may have different meanings in different native tongues. As well as the challenge of typological errors or slang Arabic: "**حلووو ، منتاز، جدن**" etc.

Table 1. English words translated to Saudi dialects

English word	MSA	Hijazi dialect	Najdi dialect
What	ماذا matha	إيش aish	وش wish
Window	نافذه nafitha	طاقه taqa	شباك shobak
Leave it	أتركها otrukha	سيبها sebha	خلها khalaha

2.3 Clustering Analysis

Clustering techniques allow companies to determine the opinion of customers from social media data accurately. As mentioned above, such clustering can be implemented by using both supervised and unsupervised clustering techniques. A wide range of studies has used clustering techniques to extract Voice of Customer using data obtained from Facebook, Twitter, TripAdvisor, and other social media websites. These include Munoz et al. (2019), Sezgen (2019), Aguwa et al. (2017), Pudaruth et al. (2018), and Bai (2011). These studies successfully develop models that analyze unstructured customer data to extract inherent opinions. Agglomerative clustering is the most common hierarchical clustering used to group objects in clusters based on their similarity. The ultimate result is a dendrogram, which is a tree-based representation of the items. (Datanovia,2018). Because of its advantages, hierarchical clustering is also applied in sentiment analysis. These include studies by Suresh and Raj (2017) and Kumar and Kumar (2019). In both studies, the researchers use the algorithm to analyze Twitter data. Both studies find the algorithm effective and efficient. Notably, Kumar and Kumar (2019) report an accuracy level of 79.8%.

while some research was done on Sentiment Analysis of Arabic Dialects, to the best of the author's knowledge, the only studies that could be identified were on the Egyptian dialect like (Shoukry and Rafea 2012); (El-Beltagy 2013), the Jordanian dialect like (Abdulla et al. 2013), or on the Emirati dialect (H. AlSuwaidi, 2016). Although some work was done on the general Saudi dialect (Al-Thubaity et al., 2018), the research has not covered a vast majority of Saudi dialects, which has not received adequate attention when it comes to Sentiment and Clustering Analysis. Second, to the best of the author's knowledge, there are no research publications that tackle bilingual sentiment and clustering analysis on bilingual text corpus in English and Arabic. The closest research to contextually analyze bilingual texts was done by (Alqaryouti et al., 2019). They collected data in English and Arabic but only focused on the data written in English during the sentiment analysis.

3. Research Methodology

The proposed methodology was systematically constructed based on the nature of the data and the aim of the research, as shown in figure 1. The total data for Saudi and non-Saudi customers was 351 collectively from Skytrax and Twitter post-cleaning. The reason for choosing these data sources is that non-Saudi customers are more prone to leave reviews on an airport reviewing website. In contrast, Saudi customers are usually vocal on Twitter regarding reviews for practically everything (Stats, 2021). Web-scrapping the data required two software, Octoparse, and Python. The data extracted from Skytrax followed Octoparse as it supported English, Whereas the data extracted from Twitter used the Selenium library in Python, which supported Arabic. Data cleaning and filtering were used programmatically to remove duplicates, empty values, and unwanted tags and then saved the data to an excel file. After that, each tweet was carefully filtered by reading and matching the search topic and deleting the tweets unrelated to the research objectives. After the dataset became ready, a trial run was implemented using a training data set, and performance was evaluated based on expert judgment. Once sentiment and clustering analyses were performed, the resulting service categories were ranked from most favorable to least favorable services provided.

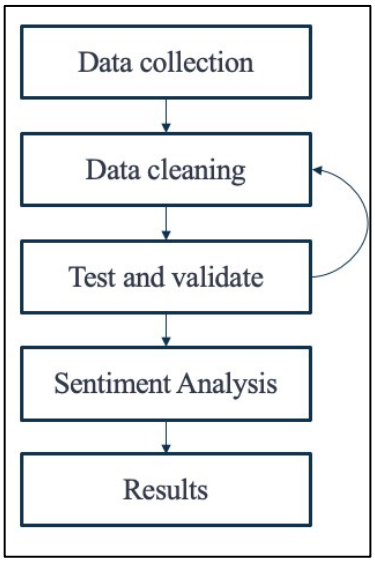

Figure 1: Methodology framework

4. Data Collection

The study was conducted by first collecting raw verbatim data from customers in Arabic and English of the three busiest international airports in Saudi Arabia (KKIA in Riyadh, KAIA in Jeddah, and KFIA in Dammam). The customer reviews were extracted from the organization complaint database, the travel review platform Skytrax, and the social media platform Twitter using web-scrapper tools Octoparse and Python. Octoparse was used to extract the customer reviews written in English, whereas Python was used to extract the customer reviews written in Arabic. Both workflows and code are illustrated in the below Figures 2 and 3.

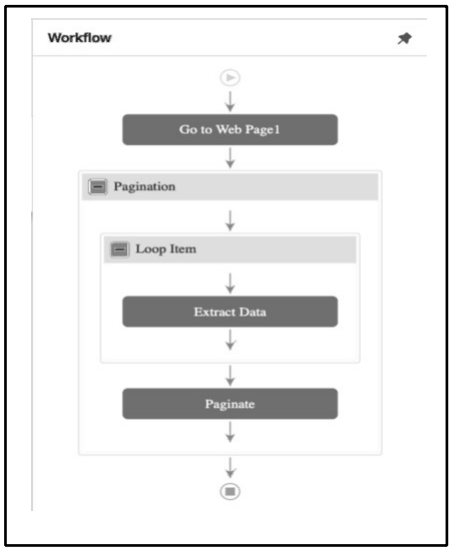

Figure 2. Octoparse software web scrapping workflow.

```
In [40]:
def save_tweet_data_to_csv(records, filepath, mode='a+'):
    header = ['User', 'Handle', 'PostDate', 'TweetText', 'ReplyCount', 'RetweetCount', 'LikeCount']
    with open(filepath, mode=mode, newline='', encoding='utf-8') as f:
        writer = csv.writer(f)
        if mode == 'w':
            writer.writerow(header)
        if records:
            writer.writerow(records)

In [100]:
def collect_all_tweets_from_current_view(driver, lookback_limit=1000):
    """The page is continously loaded, so as you scroll down the number of tweets returned by this function will
     continue to grow. To limit the risk of 're-processing' the same tweet over and over again, you can set the
     `lookback_limit` to only process the last `x` number of tweets extracted from the page in each iteration.
     You may need to play around with this number to get something that works for you. I've set the default
     based on my computer settings and internet speed, etc..."""
    page_cards = driver.find_elements_by_xpath('//div[@class="css-1dbjc4n"]')
    #print("cards_view")
    if len(page_cards) <= lookback_limit:
        print(len(page_cards))
        return page_cards
    else:
        return page_cards[-lookback_limit:]

In [70]:

def extract_data_from_current_tweet_card(card):

    try:
        user = card.find_element_by_xpath('.//span').text
    except exceptions.NoSuchElementException:
        user = ""
    except exceptions.StaleElementReferenceException:
        return
    try:
        handle = card.find_element_by_xpath('.//div[@class="css-1dbjc4n r-18u37iz r-1wbh5a2 r-1f6r7vd"]').text
    except exceptions.NoSuchElementException:
        handle = ""
    try:
        """
        If there is no post date here, there it is usually sponsored content, or some
        other form of content where post dates do not apply. You can set a default value
        for the postdate on Exception if you which to keep this record. By default I am
        excluding these.
```

Figure 3. Sample of Python code using Selenium for web scrapping

5. Sentiment and Clustering Analysis and Results

5.1 Sentiment Analysis

A sample of the customer reviews database in English and Arabic after implementing Sentiment Analysis, with a sample size of 351 reviews in total, randomly selected from 2017-2021, is shown in Table 2 and Table 3.

Table 2. Sentiment Analysis on English reviews

REVIEW TEXT	Polarity	Agreement	Subjectivity	Confidence	Irony
| I have travelled to a lot of airports but the service provided at Riya	N	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
Terminal 1 - Other Airlines. My flight was to depart 1850, so I chec	P	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
I have been a regular traveler from Egypt (my homeland) and Riyad	N	AGREEMENT	SUBJECTIVE	92	NONIRONIC
| Mess, long waiting for no reason, alot of redundant stops, official	N	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
I am an Indian but my parents live in Riyadh. I visit them during my	Po	AGREEMENT	SUBJECTIVE	98	NONIRONIC
Not Verified | | I always have a bad experience in Riyadh Airport. Not	P	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
| I was expecting an Airport in Saudi Arabia to be decent, but to my	N	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
Old airport stuck in the past where the building and infrastructure s	P	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
Faced with large queues upon reaching passport control and once th	NEU	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
Worst airport in the Gulf. When travelling during peak seasons, such	NEU	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
Used Riyadh International Terminal last week and, after reading pas	P	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
Riyadh International Terminal is one of the worst airports I've ever s	N	DISAGREEMENT	SUBJECTIVE	83	NONIRONIC
The major problem with this airport was the waiting time to receive	N	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
Used the new Terminal 5 for domestic flights, and was impressed b	P	AGREEMENT	SUBJECTIVE	98	NONIRONIC
Landed at about 3 am from an Abu Dhabi flight. Although the airpor	P	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
Whether one has an adequate experience at Riyadh airport is largel	NEU	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
It was a huge airport. Modern enough, beautiful water-fountain insi	P	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
Fastest and smoothest transit I have ever had! It took me less than	P	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
Since I flew Saudia last year so I happened to be transiting at Riyadh	N	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
This is a very old airport and it is put to shame by others in the regic	N	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
Worst airport I have ever had the misfortune to travel from and to. I	NEU	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
One of the worst with respect to airport operation management an	P	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
This airport is a complete mess. The airport administration complet	N	DISAGREEMENT	SUBJECTIVE	83	NONIRONIC
Over the past year there have been marked improvements at this ai	P	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
Being a resident of Riyadh I use this airport a lot and it's horrific. Lo	NEU	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
I have had reason to use Riyadh KKIA airport several times recently.	P	AGREEMENT	SUBJECTIVE	98	NONIRONIC
Unfortunately navigating Riyadh airport is a necessary evil for acces	N	AGREEMENT	SUBJECTIVE	100	NONIRONIC
CDG-Chennai and return July 30 and August 7th. On my way to Chen	NEU	DISAGREEMENT	SUBJECTIVE	94	NONIRONIC
Really I am not sure why this airport got such poor reviews. Curbside	P	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
Customs is slow they stopped to talk about 2 to 3 mins after every 3	N	AGREEMENT	SUBJECTIVE	92	NONIRONIC
Being a resident of Riyadh I frequently travel through King Khalid Int	P	DISAGREEMENT	SUBJECTIVE	92	NONIRONIC
I had a 10 hour connection between flights from Delhi to London. In	P	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
I've spent many years in Riyadh and I'm still prepared to drive over 3	N	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC
Frequently fly through KKIA still the same. Some of the services have	P	AGREEMENT	OBJECTIVE	100	NONIRONIC
Don't expect to get your bags first because you are a first class or bu	NEU	DISAGREEMENT	SUBJECTIVE	86	NONIRONIC

Table 3. Sentiment Analysis on Arabic reviews

N	8تساهل موظفي أمن #مطار_الملك_فهد بالدمام مع الكثامة وكذلك الأشخاص الذين يقفون أمام بوابة قدوم الرحلات في مظهر غير حضاري وكذلك غير محترم وظوهم بسبب المحافظة والحرج للمسافرين القادمين خصوصا العوائل ـ مشكلة تحتاج إلى حوار ومتابعة مستمرة من إدارة المطار
N	يستاهل #مطار_الملك_فهد_الدولي #مطار_الدمام#
P	نفسيا اتاح لهذا المطار ـ فيه طاقة وحيوية وهندسته المعمارية أنيقة #مطار_الملك_فهد بالدمام فخم وضخم وتصميمه جميل لكن ماعيه حيلة المفروض انه مطار دولي لكن بالواقع هو مطار داخلي مع كم رحلة دولية وتصهم ارتزيت
NEU	بقيت سنوات طوال استخدم مطار البحرين و#الظهران_الخليج ... نسبت #مطار_الدمام لقلة طويلة . كان من مميزاتهم وأختيارك بسيارة ليموزين من باب بيتك Quote Tweet م . خليل فزاع
P	تساهل #البحرين مطارها الحديث. ومطاعمها وأهلها من كل مكروه
P	مقطع فيديو يظهر جانباً من صفيات التعليم المستمرة لجميع مرافق #مطار_الملك_فهد، التي ينفذها فريق متخصص في التعليم، ويشمل على أدق التفاصيل مثل تعليم جهاز لتسجيل البصمات للمسافرين باستمرار، وتعليم "الكوترات" والأشعة والمواجهز المختلفة #COVID---19 #مطارنا_فخر_الوطن #أقوبها
P	... جهود جبابه تقوم بها الدولة أعزها الله اقدم عدت من دبي عبر مطار الملك فهد بالدمام ، شاهدت الإنجاح من قبل القادمين الى المملكة من جميع الجنسيات ، وذلك للإجراءات الطبية التي أوجدة على القادمين لتكشف الاصابة من ال ألزيمة #مطار_الملك_فهد#
P	.. ليش دخول الحمام (الكبينة) في مطارنا يعتبر تحدي لكتير الاشخاص ... ؟ اعتقد ان المسافر يدفع ١٠ ريال تظهر هذي الخدمات ... تنتهي خدمات اللبق فيها كمسافرين #مطار_الملك_فهد#
N+	مسافر المنتظر ومنكثير دائماً أحنا أولى بنظافة مطارنا وبلدنا ؟؟ #مطار_الدمام#
N	#مطار_الملك_فهد_الدولي# عظيم رائعة وهو مانشوفه مؤخرا في #مطار_الدمام من زيادة في الرحلات المباشرة ووجهات جديدة مضافة مؤخرا وهو ماكنا نفتقده كسكان في المنطقة الشرقية ومملكتنا في البحث عن الرحلات المباشرة بعيدا عن "الكوترزيت مطار الملك فهد الدولي استقبل #مطار_الملك_فهد_الدولي الرحلة الافتتاحية الثانية لهذا اليوم، وذلك بتدشين أولى رحلات طيران الجزيرة والتي بدأت بتسيير ثلاث رحلات أسبوعية بين الكويت والدمام نتمنى لهم كل التوفيق
P	سبق وأن كان للأخ عبداللطيف موظف ايجابي جداً معي في #مطار_الدمام كذلك سفري على #الخطوط_السعودية ـ قاسم الحميد عبداللطيف الفحطاني في مطار الملك فهد بالدمام نموذج للموظف الحقيق في طريقة التعامل الخلاصية مع الركاب، والأسلوب المثالي المحترم الذي ساعدنا مثل هذه النماذج في جميع مطارات المملكة
P	

A total of three expert judges were assigned to each airport to annotate the reviews manually, and the average among the three was considered. The reasoning behind taking the average is due to the notion that the review interpretation may vary from one individual to another. For example, if a singular review scored two negatives and one neutral, it will be considered as negative, and so on. This is true for both English and Arabic databases.

5.2 Clustering Analysis

The expert judges were also asked to cluster the categories based on a drop-down list of the airport's essential services and a vacant slot labeled as "other" to propose new dimensions of services if necessary. Applying clustering analysis on the bilingual database resulted in promising statistics. Figure 4, Figure 5, and Figure 6 show a graphical representation of the number of customers' sentiments based on clusters:

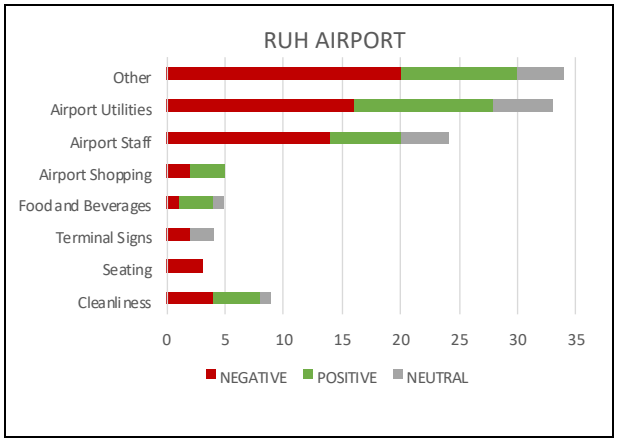

Figure 4. Riyadh airport Clustering Analysis results

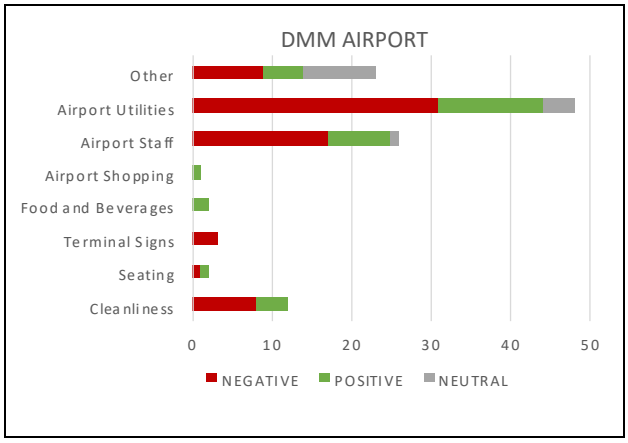

Figure 5. Dammam's airport Clustering Analysis results

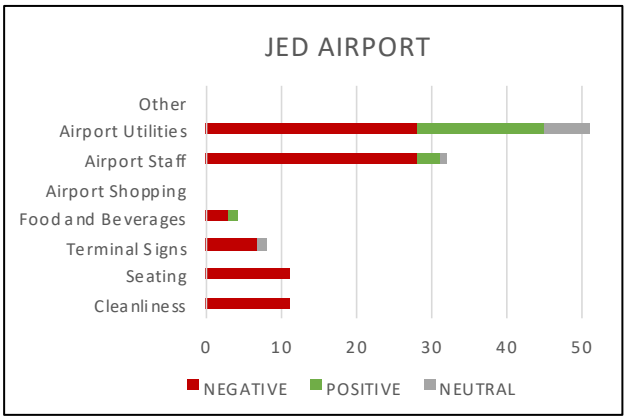

Figure 6. Jeddah's airport Clustering Analysis results

5.3 Sentiment and Clustering Analysis correlation results and discussions

Figure 7 displays the comparison of the number of sentiment and cluster analysis results in each airport per customer review. The graph shows that in DMM airport, most reviews are about the airport utilities, expressing more negative than positive reviews. In JED airport, customers express their concerns most with airport staff and an appreciation of airport utilities. Furthermore, in RUH airport, customers seem to favor the airport's cleanliness and utilities and the slightest concern with the staff.

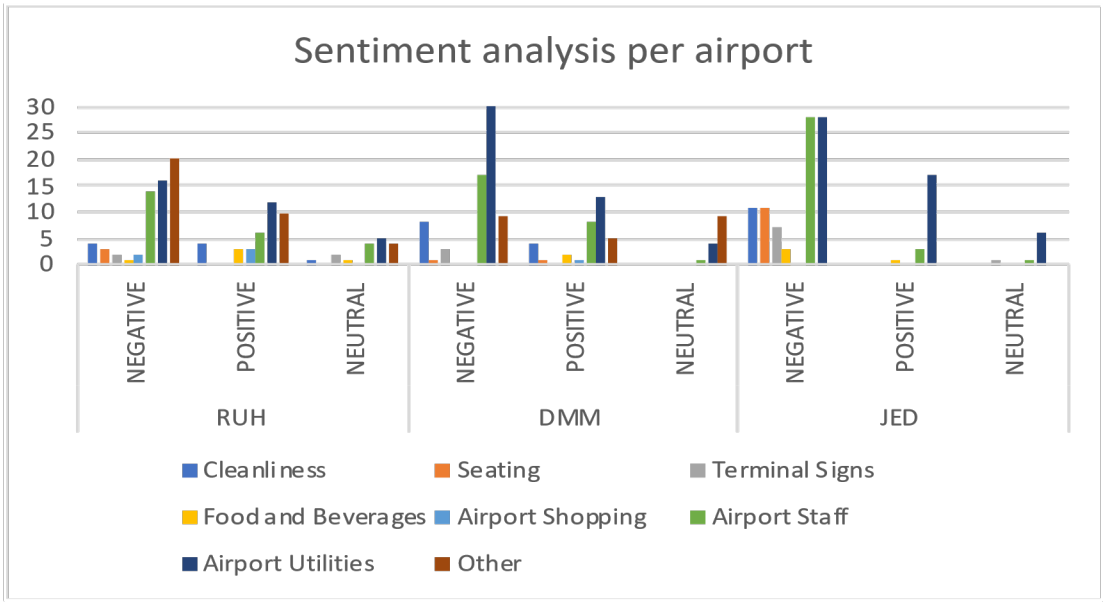

Figure 7. A comparison of the overall sentiments of customers between DMM, JED, & RUH airports.

6. Conclusion

This research provided a method for assessing conversational Arabic and English from social media customer reviews on selected international airports by enhancing and evaluating the sentiments behind reviews left on social media platforms such as Skytrax and Twitter. Experiment results in our approach, which worked and were tested on Modern Arabic language as well as English, show that the approach can detect subjective internet slang in social media, that

is represented by only one word or by several words as a whole sentence, as well as classifying the polarity of these subjective terms with a high degree of accuracy. Synthesizing with past research done on Arabic textual analysis, the challenge of analyzing informal Arabic used in everyday language was remedied by assigning expert judgers to thoroughly analyze the reviews and annotate each review with its sentiment and classify it based on the airports' services.

For further research, an algorithm model that can be developed into software could potentially fasten up the bilingual sentiment and clustering analysis by introducing a bag of words and machine learning. The software could be developed to also listen to the customer's voice in real-time, prioritize unfavorable remarks, and enhance brand reputation while preventing customer churn.

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Biographies
Haya Altajel is a senior associate consultant and head of the consulting department in Mushar management consulting group in Riyadh, Saudi Arabia. Eng. Haya holds a Bachelor of Science degree in Industrial Management from Alfaisal University and a Master of Engineering and Systems Management degree from Alfaisal University. She has been recognized for her work in a waste minimization project that saved the company half a million dollars annually in her senior capstone project by designing a diverter for seven production lines. Eng. Altajel is certified from Harvard Business school's CORe program, which involves data analytics, Economics for managers, and financial accounting.

Dr. Faisal Alotaibi is currently an Assistant Professor at the Department of Engineering, Alfaisal University, Saudi Arabia. He obtained his Ph.D. in Industrial Engineering at Wichita State University, United State, in 2016. He did his First Degree in Electronics and Computer Engineering in 2012 at Bowling Green State University, United State. He also obtained his Master of Industrial Engineering in 2014. His areas of interest are Data mining, Statistical analysis, and Quality Models.