Discourse-based Opinion Mining of Customer Responses to Telecommunications Services in Saudi Arabia during the COVID-19 Crisis

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***Abstract*—This study used opinion mining theory and the potentials of artificial intelligence to explore the opinions, sentiments, and attitudes of customers expressed on Twitter regarding the services provided by the Saudi telecommunications companies during the COVID-19 crisis. A corpus of 12,458 Twitter posts was constructed covering the period 2020–2021. For data analysis, the study adopted a discourse-based mining approach, combining vector space classification (VSC) and collocation analysis. The results indicate that most users had negative attitudes and sentiments regarding the performance of the telecommunications companies during the pandemic, as reflected in both the lexical semantic properties and discoursal and thematic features of their Twitter posts. The study of collocates and the discoursal properties of the data was useful in attaining a deeper understanding of the users' responses and attitudes to the performance of the telecommunications companies during the COVID-19 pandemic. It was not possible for text clustering based on the "bag of words" model alone to address the discoursal features in the corpus. Opinion mining applications, especially in Arabic, thus need to integrate discourse approaches to gain a better understanding of people's opinions and attitudes regarding given issues.**

Keywords—Artificial intelligence; collocate analysis; COVID-19; discourse; opinion mining; vector space clustering

I. Introduction

In recent years, millions of users all over the world have been using social media platforms and networks in an unprecedented manner as channels for expressing their views and commenting on different issues [1, 2]. In many ways, these platforms and networks have gained such legitimacy that they have become an integral part of modern life. In the face of the increasing influence of social media networks in modern societies, institutions and organizations have begun to explore people's attitudes and responses to their policies and decisions as reflected on social media networks [2, 3].

Social media networks are used extensively to express trends and ideas within society due to their potential to offer a dialogue based on equality between the individual, the elite, and the masses; thus, the elite is no longer playing its former role in shaping and mobilizing public opinion [4, 5]. Social networks have transformed and changed from being just a means of communication between individuals and groups, or even conveying the news or commenting on it, to a means of addressing various issues and provoking reactions based on the tremendous ability to spread messages. Indeed, sometimes news is transmitted from social networking sites (Facebook, Twitter) to newspapers, satellite programs, and official media, increasing the impact and spread of these sites [6]. Modern technologies and the information revolution have provided ease of broadcasting to all at low cost, resulting in the emergence of many actors. Indeed, anyone, even those lacking knowledge, competence, and qualifications in the relevant field, can express points of view and prejudices through social media, transmitting and using images, videos, and publications [7, 8]. In this regard, in recent years there has been increasing interest among academics, politicians, and marketing agencies in the ways social media networks and platforms can be used to measure public opinion in an approach known as opinion mining [9, 10].

However, in Arab countries, including Saudi Arabia, the potential of opinion mining has not yet been fully exploited in relation to social media content. The failure to consider people's responses and sentiments concerning given issues can lead to serious problems and challenges for organizations and institutions. Thus, this study seeks to propose a reliable model of opinion mining that takes into consideration the discoursal properties of social media language, as well as the unique linguistic features of Arabic. It does so through an empirical analysis exploring and identifying the opinions, sentiments, and attitudes of Saudis regarding the services provided by telecommunications companies during the COVID-19 pandemic expressed on Twitter. The study sets out to answer two major questions: What were Saudis' opinions of and responses to telecommunications services during the COVID-19 lockdown? How can discourse-based approaches be integrated in data mining studies to offer a reliable conceptual analysis of people's opinions and sentiments as expressed on social media networks and platforms? To address the research questions, the study employed a corpus of 12,458 Twitter posts covering the period 2019–2021. The rationale is that Twitter is one of the most popular social media networks in Saudi Arabia and it was the most preferred venue for Saudis to express their views during the COVID-19 lockdown.

A. Background

During the COVID-19 pandemic, there was an urgent need for reliable and effective telecommunications services that could address the increasing demand for non-traditional methods of connecting people and ensuring businesses and government agencies performed properly. The three telecommunications companies operating in the Kingdom of Saudi Arabia (STC, Mobily, and Zain) announced different initiatives to improve their performance and increase their ability to address the needs of their users and institutions throughout the Kingdom. These initiatives included incentive packages for students, internet coverage in remote areas, and free internet access for the social distancing application “Tawakalna”. The telecommunications companies announced their commitment to meeting business and private demands, whether in terms of aiding the fight against the epidemic or facilitating the work of economic sectors and supporting citizens.

In education, for instance, the telecommunications companies released an initiative whereby students were given free access to the “Your Lesson” educational platform administered by the Ministry of Education. This was meant to enable students to learn remotely with the shift from face-to-face education to distance learning. Through this initiative, the telecommunications companies intended to provide support for the local community and fulfill their social responsibilities under the exceptional circumstances suddenly being experienced in the Kingdom and globally. The initiative was also a continuation of the telecommunications companies' support for the education sector in the Kingdom, given the recognition of its importance in policy and the right of all to receive an education. The “Your Lesson” platform was launched by the Ministry of Education when it suspending in-person teaching hours and switched to distance learning at the beginning of the pandemic. More than two million students enrolled in government schools, their parents, and all those in charge of the educational process could browse the platform for free, with no effect on their data usage or allowances provided by their cellular lines or home internet subscriptions.

During the COVID-19 pandemic, the Saudi Communications and Information Technology Commission (CITC) was keen to issue a set of decisions that would contribute to ensuring the safety of citizens and residents in the Kingdom, and it launched many initiatives to enable the communications and information technology sector to perform its role in facing the pandemic. The CITC developed an action plan that would assure the performance of its tasks and mitigate the effects of the pandemic. The measures included cooperation with the competent official authorities in the country to approve the import, customs release, and field inspection of shipments of communications devices, equipment, and spare parts. The extraordinary circumstances at the time highlighted the importance of the telecommunications sector and its role in empowering other sectors through the capabilities it provides. These include facilitating links between ministries, companies, institutions, and even individuals.

Despite the policies and initiatives adopted by the CITC, telecommunications companies faced a series of complex challenges during the COVID-19 pandemic in maintaining business sustainability and continuing to serve customers who were confined to their homes in lockdown. Moreover, they had to address the pressures of hugely increased consumption as demand for internet access on mobile networks exceeded all expectations. Not only did many employees start working remotely, but also the rates of data consumption related to entertainment increased among people unable to leave their homes.

B. Theoretical Framework

Opinion mining is a field of research in natural language processing (NLP) that includes data mining, text mining, and internet mining [11]. Research in this field extends beyond computer science to business management and sociology due to its importance for business and society [11]. Its significance has become increasingly evident with the development of social media platforms such as Twitter and Facebook [12, 13]. Opinion mining is the process of analyzing data from different perspectives and discovering anomalies, patterns, and correlations in data sets that are insightful and useful for predicting outcomes that can help users make informed decisions [14, 15]. Opinion mining refers to the use of NLP, computational linguistics, and textual analysis to reveal positive, negative, or neutral sentiments and attitudes toward given issues or products through the extraction of useful patterns from textual data, and the categorization and interpretation of data using certain analytic techniques [16, 17].

The underlying principle of opinion mining is that people tend to have biased opinions, so the aim is to build a system that analyzes individuals’ feelings and opinions on certain topics and to identify what they want from a product, service, or event [18]. Data analysis is thus the process of inferring, measuring, or understanding people's opinions of a product, service, or brand in the marketplace. People express their opinions by texting images, sending personal messages, and commenting, increasingly on social media networks, such as Twitter and Facebook. Companies and governments can use the data produced by social media companies to measure opinions on a particular topic or product. In this process, opinion mining can be exploited to interpret the nuances of customer reviews, financial news reports, social media, etc. [19]. Artificial intelligence has played a key role in almost all opinion mining applications [20, 21], with algorithms specifically designed for the analysis of people’s opinions on social media sites.

II. Literature Review

In recent years, both research and industry have paid special attention to the huge amounts of data available on the internet [22, 23]. The sources of data can be user or customer ratings of specific products, posts, comments, tweets, news articles, and various types of information on web pages. With the advent of social media, people started talking more openly about their experiences with products and services online through blogs, social media stories, reviews, recommendations, reports, hashtags, comments, direct messages, news articles, and so on [24]. Such online interactions leave a digital fingerprint of an individual's expression of the experience. Hence there arose a need to adopt NLP approaches to organize what is circulated on social media sites, and to treat it in a short time with the least effort and cost [25, 26].

From a business point of view, opinion mining has proved useful for businesses and organizations. By analyzing users' opinions through surveys or their interactions (posts or comments about a particular product) on social media sites, companies can respond to their customers' needs, and improve their services and products to suit those needs [14, 27]. The underlying principle is that by drawing on a wide range of opinions and expressions, businesses and brands can accurately capture the voice of their target audience, understand market dynamics, and even identify their market position among end users [28]. Pazos-Rangel et al. argue that opinion mining not only helps companies and businesses understand the current context of a particular topic, but also enables them to predict the future, as well as using the information contained in the texts to calculate positive/negative feedback, which is an important indicator in decision-making processes [29]. Liu considers that adopting opinion mining and sentiment analysis techniques can aid companies, enterprises, and governments in the difficult process of making sound decisions by providing information on people's opinions and experiences of the products, services, or policies concerned [14].

In business, opinion mining has been widely used in marketing, customer services, and other areas to increase revenue, improve spending, target new customers, provide the best customer service, and address customer needs through analysis of the opinions, sentiments, and attitudes of users and customers related to services and products. Bal et al. assert that opinion mining has become one of the critical success factors for the growth and survival of organizations in an era of unprecedented global competitiveness [30].

According to Zvarevashe and Olugbara, there are many examples of the successful use of opinion mining to improve the quality of products and services. Manufacturers use opinions about a product or service as a reaction to make decisions aimed at improving quality [31]. Opinion mining and sentiment analysis are used to analyze the opinions of consumers or online customers to determine the advantages and disadvantages of a product or service, and this process saves the money that would previously have been spent on gathering information by other means.

Opinion mining has been closely associated with marketing research [32, 33]. This is one of the fields that uses sentiment analysis techniques to analyze consumer trends in relation to certain products or services, and it is also used to determine the success of an advertising campaign and study "what an individual needs from products or services that are not available in the market"; thus, it is highly significant and if used in the right way economically, it will be of great benefit to businesses [34-36].

Various opinion mining methodologies and techniques have been developed based on different models, including polarity, automatic detection, and aspect-based approaches. In the polarity model, sentiments and attitudes are automatically identified and categorized (positive, negative, neutral). In some cases that require high accuracy, the classes of polarity are expanded, encompassing very positive, positive, neutral, negative, and very negative [17, 37].

In the emotion detection model, the goal is to identify emotions, such as happiness, fear, anger, etc. Dictionaries tend to be used in this approach (listing words with their corresponding emotions), but automatic learning algorithms can also be employed [17]. Here it is worth noting that when using dictionaries, the problem of the relation between different emotions and words arises, in particular that people can express their emotions in different ways [38].

In aspect-based opinion mining applications, the goal is to extract both the entity described in the text (in this case, attributes or components of a product or service) and the sentiment expressed toward such entities [39]. According to Moghaddam, the premise is that extracted aspects and estimated ratings clearly provide detailed information for users to make decisions and for suppliers to monitor their consumers. [40].

Despite the popularity of these methodologies and models, one major problem remains. Put simply, they do not consider the context of the texts because this adds to the complexity of the models and increases the time and cost of processing [41]. This study addresses the gap in the literature by proposing an integrated opinion mining model that takes into account the contextual aspects and features of the texts under investigation.

III. Methods, Data and Procedures

To explore and identify the opinions, sentiments, evaluations, and attitudes of Saudis regarding telecommunications services during COVID-19 pandemic, this study is based on a corpus of 12,458 Twitter posts over the period 2020–2021. The rationale is that Twitter is one of the most popular social media networks in Saudi Arabia. Furthermore, Twitter was the most preferred venue for Saudis to express their views and sentiments during the COVID-19 lockdown. The study is confined to tweets written in Arabic. The data include posts in both Modern Standard Arabic (MSA) and Saudi spoken Arabic. The latter is not usually considered in NLP applications in Arabic as it has typically been considered a lower variety than MSA. With the emergence of social media networks, however, colloquial and spoken dialects of Arabic have become highly prevalent. It is thus appropriate to include all the Arabic varieties in Saudi Arabia to undertake a thorough classification of Saudis' responses.

Different methodologies are used for opinion mining, including rule-based methodologies and methodologies based on machine learning techniques. In rule-based methodologies, determining polarity and identifying the sentiments and attitudes of the users are based on manually defining a set of rules in which lexicons of groups of words and expressions with corresponding feelings are predefined [42]. Two strings are usually created that directly identify polarity. Positive words can include good, great, and reliable. Negative words may include bad, failed, and unreliable. The words expressing positive feelings and the words expressing negative feelings are then counted and calculated. If the number of positive words exceeds the number of negative words, the result is a positive feeling, and vice versa; in the event of equality, the result is neutral [43].

In machine learning methodologies, no hand-written rules are developed. The premise is that opinion mining is first a clustering issue. Thus, machine learning algorithms are used for data clustering, based on no prior assumptions about the data [44]. Text clustering is the process of automatically grouping natural language texts according to an analysis of their informational content using machine learning algorithms [45]. Clustering is one of several computational systems for carrying out data mining tasks. Document clustering has proved successful in many important operations for data mining, including NLP, feature extraction, annotation, and summarization.

Text clustering underwent considerable development in the 1990s when it emerged as a subtask of information retrieval (IR) applications. The hallmark of that development was a dramatic improvement in the effectiveness of text clustering systems. The last two decades have witnessed an unprecedented revolution in the rise of mechanized solutions for organizing the vast quantity of unstructured digital documents and of powerful tools for turning an unstructured repository into a structured one [46]. The main bulk of clustering systems or approaches can best be described under the heading vector semantics (VS) or vector space clustering (VSC). Semantic structure is essential for clustering applications. The underlying principle of VSC is that it measures or computes semantic similarity between the documents to be clustered [47].

For the purposes of this study, VSC was conducted based on the lexical semantic properties of the linguistic content of the tweets. VSC is one of the most appropriate classification methods for opinion mining applications [48-50]. The steps are described in the following sub-sections.

A. Text Preprocessing

Texts are first chopped into a list of tokens representing them. This is usually done in a straightforward way, removing punctuation and non-alphabetic characters and all extraneous material. This has the effect of converting texts into what is called a “bag of words,” in which context and word order are not considered.

B. Removing Function Words

One of the main challenges with text clustering applications is the difficulty of extracting the semantics of natural language texts. This is usually due to the occurrence of irrelevant terms within documents. In text clustering, function words are classified as irrelevant. Thus, text clustering is typically based on what can be called keyword indexing. This is the selection of only index terms, or what are traditionally called content words, within documents. The main assumption in removing function or grammatical words is that they do not carry lexical significance, so it is essential to remove them. Function words are described as “noisy” and are not considered in the analysis. Hence, they are best described as irrelevant features. The retention of such irrelevant variables or features is useless and even misleading in clustering applications.

C. Stemming

After removing the function words, stemming is carried out. Stemming can broadly be defined as the process of conflating semantically equivalent word variants into the same root by removing derivational and inflectional affixes [51]. The basic concept of stemming is that words with the same stem or root referring to the same concept must be grouped under the same form. Stemmers are thus designed to conflate together all and only those pairs of words that are semantically equivalent and share the same stem [52]. The premise is that word endings do not have essential meanings in themselves and thus their removal is useful in text clustering applications. Conflating words that have the same root into a single term improves the performance of clustering systems by reducing the size and complexity of the data in the system [45].

Various stemmers have been developed in English. These have been concerned particularly with suffixes, i.e., derivational and inflectional endings attached to words. As noted by Stageberg, derivational suffixes affect the part of speech (act, active, activate, activation) and they can be piled up [53]. That is, it is possible to add more than one suffix to one word. Inflectional suffixes, in contrast, do not change the part of speech, but indicate a grammatical function or change within the word (play → plays, cat → cats, big → bigger). Inflectional suffixes cannot pile up, the only exception being the plural followed by the possessive. The attachment of derivational and inflectional morphemes typically leads to an increase in word variant forms. According to Stageberg, derivational morphology is one of the most means of creating new words. From an IR viewpoint, this is a problem since the increase in word variant forms leads to complexity in the data in the system. As a result, word variant forms affect the effectiveness of IR systems and it is necessary to employ stemming algorithms that can reduce the size and complexity of the corpus by conflating semantically related variant forms in a common term.

English stemmers are not appropriate for Arabic due to the morphological and linguistic differences in the languages. Arabic has its own unique morphological system that is completely different from English. For the purposes of the study, the light-based stemmer (Light10) was used.

D. Data Representation

For data representation, a matrix is built including all the lexical types of the posts. A data matrix is simply a quantitative data table that summarizes the frequencies of each word within the documents, where the documents are the rows and the words or lexical types are the columns. A collection of 500 documents can be all represented in just one matrix. The matrix includes all the lexical types in the corpus after removing the function words and carrying out stemming. The lexical frequency is weighted. A matrix of this kind is called a row vector matrix and can be represented as X_{ij}, where i represent rows and j represents columns. Thus, the data matrix X_{ij} is a representation of rows (tweets in this case), and columns (lexical types).

One problem with such a matrix is variation in document length. Posts in Twitter tend to vary in length, some being long and others very short. Variation in document length can have serious consequences for the reliability of classification applications. If not addressed, there will be a negative influence, since the classification will be based on the length of documents not the lexical properties [47]. All documents need to contribute significantly and equally to the distance in VSC, so that the distances are equitable. Otherwise, the differences between very long documents will dominate the distance calculation. One way of addressing this problem is to compensate the short texts for length through a process called normalization of text length [54]. Cosine normalization is used for this purpose. In this process, all row vectors of the matrix are transformed to have unit length and are made to lie on a hypersphere of radius 1 around the origin so that all vectors are equal in length. Accordingly, variation in the lengths of documents, and correspondingly of the vectors that represent them, are no longer a factor [55]. This has the effect of representing the variables equally in the matrix.

In this study, having carried out the normalization of text length, it was clear that high dimensionality was another problem that could have a negative impact on the reliability and validity of document classification. High dimensionality of the data is challenging for automatic classification systems as it is difficult to classify documents based on their lexical semantic properties when the number of dimensions is staggeringly high [56, 57]. In the face of this problem, term frequency-inverse document frequency (TF-IDF) can be used so that the classification is based on only and all the most distinctive features or variables. In our case, the datasets were reduced to the highest 200 TF-IDF variables thought to be the most distinctive features in the corpus, as shown in Fig. 1.

Then, the posts were clustered using Euclidean distance methods to identify and explore the responses of Saudis to the services of the telecommunications companies during the pandemic. Euclidean geometry is concerned with modelling the world as it is experienced. It describes the physical world in any finite number of dimensions using a distance formula [58]. Euclidean geometry has been used virtually unchanged for 2,000 years to understand physical reality. It used to be seen as a perfect model for logical reasoning. Despite its deficiencies, Euclidean geometry is still used in a range of disciplines, including the analysis of textual data.

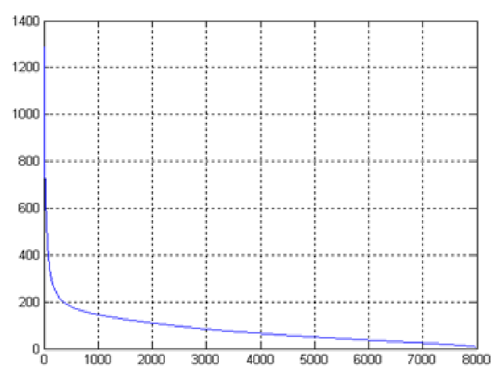

Fig. 1. Term Weighting using TF-IDF.

To overcome the limitation of machine learning algorithms in the classification process, discourse analysis methods were finally incorporated in the analysis and categorization of the data. The hypothesis here is that context is essential for understanding the polarity within the data and users' attitudes and sentiments. Failure to consider the context can result in misinterpretation of users' views.

IV. Analysis and Discussion

In this study, the data matrix was first hierarchically analyzed using Euclidean distance with four clustering methods (single linkage, complete linkage, average linkage, and increase in the sum of squares), then using squared Euclidean distance with the same clustering methods. Finally, the clustering structures were compared to determine the extent to which they agreed on the data structure.

The results showed no significant difference between the Euclidean and squared Euclidean measures. For all the hierarchical cluster analyses, optimizing both functions produced almost the same order of the proximity matrix and tree. However, the Ward clustering method worked better with Euclidean distance than with squared Euclidean distance as it gave clearer results, and the groups or classes were more clearly defined. It was also apparent that all four methods agreed on the main clusters in their clustering of the matrix rows but disagreed on the detailed structure.

Single linkage clustering was not very useful in identifying meaningful clusters for this study because of the "chaining effect" feature that characterizes it. The problem with such clustering is that the texts are chained together in a way that obscures any structure beyond sequentiality. Likewise, complete linkage was not appropriate. The two complete clustering structures were uneven, producing a large number of small-membership clusters and sometimes producing a small number of large-membership clusters.

Although average linkage clustering is considered the default method in agglomerative hierarchical clustering since it overcomes the problems associated with single and complete linkages, it was not ideal in this case because of the overwhelming tendency toward left branching. One more problem with average linkage is that some classes or groups are too small to be considered distinct classes, whereas some other classes are too large to express the dataset consistently.

Thus, Ward linkage clustering (or what is usually referred to as the sum of squares) with the Euclidean distance measure seemed to be the most appropriate because it achieved the clearest partitioning of the matrix rows. Ward clustering served the purpose of the analysis, namely to discover useful associations and meaningful groups in the dataset, and thus obtain a clearer picture of the responses of the users. The study was not only concerned with identifying the yes/no or approve/disapprove dichotomy. Rather, it sought to gain a deeper understanding of the data corpus. Using the sum of squares, it was easy to identify the number of clusters (2). The matrix rows were assigned into two clearly identified classes or clusters, as shown in Fig. 2.

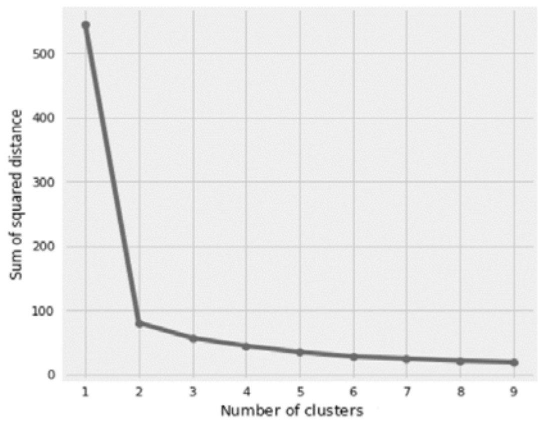

Fig. 2. Identification of the Number of Clusters.

Next, principal components analysis (PCA) was carried out. The comparisons showed a great deal of agreement in all clustering structures, supporting the validity of the results. The clustering structure most agreed on was Ward clustering with the Euclidean distance measure. The matrix rows of this structure are assigned into two groups, A and B.

A. Centroid Comparison

To measure the distance between the two clusters, centroid analysis was used, such that numerical differences between Group A and Group B specify the numerical difference between the vectors of A and B for each of the 200 variables. Based on the centroid comparison results, it is possible to determine which variables are most and least characteristic of each group, and which most differentiate them. There is too much detail here for convenient interpretation. Attention can be restricted to a smaller number of higher variance variables at the top of the tables, shown in Table I.

TABLE I. CENTROID COMPARISON

Variable index	Centroid 1 frequency Group A	Centroid 2 frequency Group B	Difference
48	2.44595E009	0.000	2.44595E009
4	2.42644E009	4.0673E006	2.42238E009
31	2.54036E009	2.79667E008	2.26069E009
65	2.91405E009	1.1363E009	1.77775E009
104	1.80511E009	6.30595E007	1.74205E009
53	4.38992E009	3.14724E009	1.24268E009
8	1.16744E009	4.12437E008	7.55E008
128	7.63672E008	9.94767E006	7.53725E008
69	9.86888E008	2.62397E008	7.2449E008
117	1.87076E009	1.15296E009	7.178E008
49	3.37362E009	2.70039E009	6.73233E008
19	1.1788E009	6.07323E008	5.71476E008
144	4.43691E008	9.60451E008	5.1676E008
5	6.67001E008	1.16991E009	5.02913E008
123	3.90971E008	8.59611E008	4.6864E008
18	0.000	3.24402E008	3.24402E008
169	8.47943E008	1.17019E009	3.2225E008
86	7.41665E008	1.04859E009	3.06928E008
98	2.92798E008	5.83877E008	2.9108E008
14	0.000	1.88799E008	1.88799E008
170	2.77724E008	4.55483E008	1.77759E008
37	2.56518E008	9.27863E007	1.63732E008
133	8.15213E007	2.43435E008	1.61914E008
109	5.88612E007	2.20095E008	1.61233E008
54	1.10216E008	2.71329E008	1.61112E008
134	1.97654E008	4.10541E007	1.56599E008
27	0.000	1.53976E008	1.53976E008
6	5.58119E007	1.64829E008	1.09017E008
89	7.12929E008	6.04511E008	1.08418E008
3	2.12619E008	1.07434E008	1.05185E008
79	0.000	9.86853E007	9.86853E007
151	1.70559E008	2.68003E008	9.74437E007
7	4.01059E007	1.33103E008	9.29971E007
184	5.98243E007	1.52622E008	9.27976E007
29	1.43507E008	2.34668E008	9.11606E007
9	1.18371E008	2.09474E008	9.11036E007
81	0.000	9.00644E007	9.00644E007
35	9.1281E007	2.32374E006	8.89573E007
2	0.000	8.86559E007	8.86559E007
147	4.71117E007	1.34375E008	8.72632E007

Based on the centroid comparison, it is clear that there are significant differences between the members of each cluster or group. A comparison of the most distinctive variables in each group reveals that the texts in Group A tend to express approval of the telecommunications and internet services, as indicated by words like good, better, free, useful, and initiative, shown in Table II.

TABLE II. DISTINCTIVE LEXICAL FEATURES OF GROUP A

Group A		
Arabic words	**Transliteration**	**English translation**
جيد	Jyid	good
أفضل	Afdil	better
مجاني	Majaani	free
مفيدة	Mufida	useful
مبادرة	Mubadara	initiative
إضافية	Iidafiatan	additional
سماح	Samah	allowance
يمكن	Yumkin	enable
حلوة	Hulwa	cool
معقول	Maequl	reasonable
كويس	Kuays	well/fine

Group B, in contrast, reflects the disapproval of the users of the services provided by the companies, as indicated by words such as poor, worst, disconnected, and complaint, shown in Table III.

TABLE III. DISTINCTIVE LEXICAL FEATURES OF GROUP B

Group B		
Arabic words	**Transliteration**	**English Translation**
أسوأ	'aswa	the worst
سيئة	Sayiya	poor
عدم	Eadam	Non
شكوي	Shakwi	complaint
فصل	Fasl	disconnect
مفيش	Mufish	Nothing
بايظ	Bayiz	Down/not working
لعنة	Laena	Curse
فاشل	Fashil	loser/failure
مو	Mw	not
لا	La	no
هدر	Hadr	waste
غلا	Ghlana	expensive

Concerning the number of the tweets in each group, it is clear that most users had negative attitudes toward the services provided by the telecommunications services during the COVID-19 pandemic. The first group includes 31% of the tweets in the corpus, while the second group includes 69%. Referring to the lexical centroids, it can be claimed that the attitudes of Saudis to the services provided by the telecommunications companies during the pandemic were largely negative. Although the statistical findings of the study give broad indications about the attitudes and sentiments of the users on this issue, it is important here to look at the discourse features of the corpus to obtain a broader and more in-depth knowledge about the data. This is shown in the collocation analysis below.

B. Collocates

This section seeks to explore the distinctive discourse features of the two groups assigned through cluster analysis. For this purpose, three key words, MOBILY, ZAIN, and STC, were selected denoting the three telecommunications companies operating in Saudi Arabia. These are shown in Table IV.

TABLE IV. FREQUENCY OF KEY WORDS

KEY WORD			**FREQUENCY**
	موبايلي	MOBILY	1486
	زين	ZAIN	1369
	إس تي سي	STC	1199

A frequency analysis of the three key words using the KWIC concordance analysis was then carried out with the two groups, A and B, to explore the discoursal and thematic features of each group.

In Group A, the three key words were associated with concepts such as shopping apps, working from home, facilitating virtual interactions, health information, access to services, social distancing, tracing apps, social connectedness, connectivity solutions, education services, and education providers, as shown in Table V.

For Group 2, the three key words MOBILY, ZAIN, and STC appeared to be associated with key concepts including service suspension, weak infrastructure, reduced network performance, congestion in mobile networks, high cost, uneconomical, high-priced, connection problems, threatened with disconnection, frustrating handling of individual complaints, remote areas, missing classes, disadvantaged neighborhoods, digital divide, poor coverage, and poor customer service. A frequency analysis of these collocates is shown in Table VI.

Based on the collocation analysis, it can be suggested that most users had negative attitudes concerning the performance of the three telecommunications companies during the pandemic. They were not happy with the high costs of the services and packages, or the connection problems that had negative implications for their commitment to classes. Many of them expressed their dissatisfaction with the companies' handling of their complaints. Others were concerned with the poor infrastructure in remote areas and disadvantaged neighborhoods. In contrast, a minority of users had positive attitudes. Referring to their tweets, they expressed their satisfaction with the services in terms of disseminating information on health, facilitating social distancing, and supporting distance learning through education platforms, and working from home. They were also happy with the initiatives and free internet services provided by the companies during the pandemic.

TABLE V. COLLOCATES IN GROUP 1

	Collocates	**Frequency**
تسهيل التواصل	facilitating virtual interactions	865
معلومات صحية	health information	775
الوصول إلي الخدمات	access to services	692
توافر الخدمات	availability of services	692
التواصل الاجتماعي	social connectedness	544
سرعة عالية	high speed	356
التباعد الاجتماعي	social distance	344
حلول الإتصال	connectivity solutions	311
الخدمات التعليمية	education services	289
المؤسسات التعليمية	education providers	257
التعليم الجامعي	university education	249
تطبيقات التسوق	shopping apps	199
العمل من المنزل	working from home	185
منصات التعليم	Education platforms	167

TABLE VI. COLLOCATES IN GROUP 2

	Collocates	Frequency
فصل الخدمة	service suspension	1968
بنية تحتية ضعيفة	weak infrastructure	1885
انخفاض أداء الشبكة	reduced network performance	1779
الضغط علي شبكات المحمول	congestion in mobile networks	1766
مكلفة	Costly	1693
تكلفة عالية	high-cost	1655
غير اقتصادي	Uneconomical	1588
غالي	high-priced	1579
مشاكل الإتصال	connection problems	1344
مهددة بانقطاع وفصل الخدمات	threatened with disconnection	1288
التعامل المحبط مع شكاوي العملاء	frustrating handing of individual complaints	1262
مناطق نائية	remote areas	1223
الغياب عن المحاضرات	missing classes	1175
الأحياء المحرومة	disadvantaged neighborhoods	1134
تغطية سيئة	poor coverage	988
خدمة العملاء السيئة	poor customer service	967

It can thus be argued that the study of collocates and discoursal properties of the data was useful in attaining a deeper understanding of the users' responses and attitudes to the performance of the telecommunications companies during the COVID-19 pandemic. It was not possible for text clustering based on the "bag of words" model alone to address the discourse features in the corpus. Opinion mining applications, especially in Arabic, thus need to integrate discourse approaches to gain a better understanding of people's opinions and attitudes regarding given issues. Arabic is one of the most widely used languages on the internet, but it has not received sufficient attention in such applications compared to other languages, particularly English. The reason for this is that it has a complex linguistic structure and its own linguistic nature, and the availability of linguistic resources on Arabic is limited mainly to dictionaries and grammar. This is one of the challenges facing researchers working in Arabic. The proposed method addresses some of the linguistic challenges in opinion mining applications in Arabic.

V. CONCLUSION

This study has addressed the issue of using the potential of artificial intelligence to explore the sentiments and attitudes of customers concerning the performance of the Saudi telecommunications companies during the COVID-19 pandemic. It is clear that most users had negative attitudes. The study has offered an integrated approach that combines VSC and discourse analysis tools to address the limitations traditionally associated with opinion mining applications. The integration of discourse analysis tools was useful in attaining a deeper understanding of the users' responses and attitudes. Although this study was limited to the performance of telecommunications companies in Saudi Arabia during the COVID-19 pandemic, the proposed method can be usefully applied in other opinion mining applications, especially in Arabic, which poses many challenges for researchers due to its unique linguistic features and lack of linguistic resources. Such issues tend to have negative implications for NLP applications in Arabic, including opinion mining.

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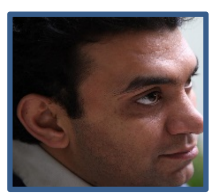

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