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Aspect Based Sentiment Analysis of Ridesharing Platform Reviews for Kansei Engineering

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ABSTRACT At present online reviews are becoming an important source for Kansei engineering of the services provided by ridesharing platforms. Kansei engineering deals with incorporating customer feedback and demands into product and service design. Thus, it is used as a tool for organizations to uplift their businesses by considering customer reviews and feedback. Customer reviews available on social media are in unstructured form; therefore, sentiment analysis is employed to extract customer's opinions in a systematic manner. In India-Pakistan, these reviews are mostly in Roman Urdu/Hindi and English, which are of great value for ridesharing platforms as a part of their Kansei engineering strategy. However, sentiment analysis cannot be performed directly on these reviews as they are mostly in Roman Urdu/Hindi. Therefore, the objective of this paper is to conduct aspect based sentiment analysis on these reviews after translating them into English for Kansei engineering of the service. Consequently, sentiment analysis is carried out to extract the most frequent features along with nouns and adjectives used by the customers to express their sentiments. We extracted prominent aspects of the service (i.e., 'Driver', 'Company', 'Service', and 'Ride') based on their highest frequencies using aspect based sentiment analysis. The customer sentiments are then clustered into these main aspects using unsupervised machine learning technique. Each aspect is further analyzed based on their polarity, which serves as an input for Kansei engineering of the service. As a result, it can facilitate ridesharing companies to enhance their businesses by improving services in accordance with customer demands.

INDEX TERMS Roman Urdu sentiment, Kansei engineering, aspect based sentiment analysis, polarity classification, ridesharing platform reviews.

I. INTRODUCTION

The technical advancements in businesses have changed the traditional business strategies from product-oriented design to a customer-oriented design by linking it with customer's satisfaction and feedback. It makes the customer's requirements as much important as other functional requirements of a successful business. Similarly, in ridesharing platforms, the customer's satisfaction is a key to their success in a highly competing market. Now, it has become a challenge for these companies to achieve maximum customer satisfaction covering all the aspects of their services like performance, pricing, ease of use, etc. The technique to integrate the customer's feedback into product and service design is known as 'Kansei engineering' [1]. The Kansei engineering aims to develop a relationship between customer's sentiments and product design parameters [2]. This will help the product to achieve maximum customer satisfaction, which in turn uplifts the company's business in the market [3].

In the past, customer opinions were obtained through questionnaires, literature reviews, interviews, and large scale web-based surveys [4]–[7]. In questionnaires and surveys, the surveyor typically tries to map the product design parameters with customer satisfaction [8], [9]. In these methods, a scale called a semantic differential scale (SD) is developed based on Kansei attributes. The scale consists of some arbitrary points to get the respondent's degree of satisfaction to evaluate the product design [10]. These methods are used to get high-quality data on a small scale. For example, in past customer sentiments about ten products were

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evaluated by only a group of seven users [11]. Therefore, the results of these interviews and questionnaires cannot be trusted. Whereas, in large scale web-based surveys, there are hundreds of online respondents. However, these responses were highly biased by the attitude and commitment of the participants.

Another important source of getting customer feedback is customer reviews available on online social networks. Customers post their reviews on social networks without any biases [12]. Thus, these reviews depict customer's sentiment in the true sense at large scale. This interactive content is of great importance for corporations, product designers, and government agencies, etc. [13]. As the reviews are enormous and unstructured, therefore, sentiment analysis is carried out to extract the sentiments conveyed by the customers about the quality of the product [14], [15]. These sentiments are then used as an input for Kansei engineering of product design and improvement, which enable the businesses to remain in market competition [16].

The ridesharing platforms are growing rapidly all over the world especially in South Asian countries like India and Pakistan during the last few years. The majority of the people do not have their own transport in this region, which contains a one-fifth population of the world. Therefore, it has raised the competition among the ridesharing companies like Uber, Careem, Ola, Taxi, Blacklane, Talixo, and Lyft. It makes them much more conscious about the quality of their services. In the India-Pakistan region, the most dominant language is Urdu/Hindi. Therefore, most of the ridesharing customers prefer to post their comments/reviews in Roman Urdu instead of English. The existing work available in literature applied the sentiment analysis only on the reviews posted in the English language [17]. Thus, it does not depict the actual sentiments of customers about the quality of service in this region. Further, the existing work on sentiment analysis in ridesharing platforms considers the service as a whole without splitting it into its key aspects, i.e., 'Driver', 'Company', 'Service', and 'Ride'. As a result, it failed to reveal which aspect of the service is adversely affecting the performance. Moreover, for Kansei engineering, we need customer's feedback for each and every aspect of the service in order to improve them according to customer demands.

The objective of this research is to carry out aspect based sentiment analysis to extract customer's sentiments from online reviews posted in Roman Urdu/Hindi and English as required for the Kansei engineering of the service. We believe that this is the first work that considers Roman Urdu/Hindi reviews along with English for the aspect based sentiment analysis of the service in the region. In this work, the target ride sharing service is Uber as it has more than 50%[1] market share in India and Pakistan. The customer reviews are extracted from a third-party platform (i.e., Facebook) instead of the company's own webpage/mobile app for maintaining their transparency. In the first step, the reviews available in Roman Urdu/Hindi are translated into English using customized APIs. Next, the sentiment analysis is carried out on combined reviews to extract the most frequent features as well as nouns and adjectives to mine the sentiments of the customers. This leads to mine the prominent aspects (i.e., 'Driver', 'Company', 'Service', and 'Ride') of the service based on their highest frequencies using aspect based sentiment analysis. This unique approach provides a comprehensive insight into the service in terms of the customer's perspective. Finally, the sentiments of the customers are clustered with positive and negative categories into these main aspects of the service using unsupervised machine learning. This classification helps to find the most discussed aspect of the company in terms of quality of service. It serves as an input for Kansei engineering of the service in order to design and improve it according to customer's demands. The main contributions of the paper are as follows.

1) This work is first of its kind as it analyzed customer reviews posted in two languages (i.e., Roman Urdu/Hindi and English) collectively for Kansei engineering of ridesharing platform.
2) We mined customers' sentiments to extract the most frequent features, nouns, and adjectives to express their sentiments in online reviews.
3) We carry out aspect based sentiment analysis to extract the prominent aspects (i.e., 'Driver', 'Company', 'Service', and 'Ride') of the service based on their highest frequencies. Later, customer sentiments are clustered into these aspects using an unsupervised machine learning approach.
4) Finally, the positive and negative sentiments of the customers are separated out for each aspect to act as an input for Kansei engineering of the service.

The rest of this paper is organized as follows. Section II reviews the related work. Section III outlines the methodology of this work. Results and discussions are detailed in Section IV. Finally, the conclusion and future work are drawn in Section V.

II. RELATED WORK

In this section, we discussed the existing work on the basis of Kansei engineering, sentiment analysis, and their applications in ridesharing platforms.

A. KANSEI ENGINEERING

The history witnessed countless research studies in the field of Kansei engineering to discover the association between product design parameters and customer intentions [18]. Kansei is a word taken from the Japanese language used to depict customers' sentiments and expressions. In recent work, Kansei engineering was carried out using different product parameters. In these studies, the researchers take the end user's opinion about mobile phones on a five-point scale [19]–[21]. The same scale with four bipolar parameters

[1] https://investor.uber.com/news-events/news/press-release-details/2020/Uber-Announces-Results-for-First-Quarter-2020/default.aspx

is used to get customer perception about home service robots [22]. Chou [11] formulates the computing with the word approach for Kansei engineering and uses a seven-point scale to evaluate customer perception. Further, the author finds out the fuzzy relationship among Kansei parameters and classify them accordingly using a questionnaire. The questionnaire surveys are extensively used for Kansei evaluation to know the customer intentions. For example, about home delivery service or product warranty. Moreover, these surveys are used to find an association between the sentiments of the user (represented by simple words in the questionnaire) and the design elements such as parameters, properties, and characteristics of the service design [23]. In [24], the authors evaluate the product by considering all important steps of product manufacturing including marketing strategies using a Kansei engineering approach. However, all these examples have a small number of respondents who are solely selected by the researchers. Thus, it does not truly represent the population and hence highly biased.

B. SENTIMENT ANALYSIS

Online reviews available on e-commerce web site and social media can solve the above-said problem [15]. Customer reviews available on these sites are increasing at a very fast pace due to rapid Internet growth [2]. Therefore, sentiment analysis is extensively used to extract and evaluate customer opinions and sentiments from these online reviews in various fields [16], [25], [26]. For example, online customer reviews are used to check people's attitudes towards ad blocking [27]. The researcher used the topic modeling approach and showed that people expressed negative attitude towards the websites that contain ads and positive attitude that do not. Similarly, online customer reviews are collected from popular e-commerce website i.e., Amazon and used to analyze the customer opinion about the "recliner" to carry out its Kansei engineering [15].

Further, the researchers used deep learning techniques to conduct sentiment analysis of product reviews available on Amazon. They developed a framework to judge a review sentence's orientation based on polarity classification [28]. Similarly, Majumder *et al.* [29] emphasized that sentiment analysis can be benefited with sarcasm detection showing the intensity of user sentiments. They used a deep neural network to build a multitask learning-based framework. Similarly, Wang *et al.* [30] identified improvement in twitter sentiment analysis by combining diffusion patterns with text messages.

C. ASPECT BASED SENTIMENT ANALYSIS

An important category of sentiment analysis is aspect based mining, which provides comprehensive opinions or sentiments about different aspects of the product or service [31]. Aspect based mining is executed in two stages, in the first stage, opinion attributes are identified and in the second stage, their polarities are figured out. A similar approach was used for review mining of restaurants to analyze customer feedback [14]. Similarly, Yang *et al.* [32] developed a deep neural network with contextual, lexical, and syntactic clues for aspect based sentiment analysis. However, Do *et al.* [33] reviewed and suggested that deep leaning techniques used for aspect based sentiment analysis achieved better accuracy but still faces challenges in data, languages, and domains.

D. MULTILINGUAL SENTIMENT ANALYSIS

With the increased use of social media throughout the world, it is not appropriate to consider users' sentiments only in English. There is a dire need to work on multilingual reviews to extract users' true sentiments. As a result, multilingual sentiment analysis is gaining attention in Chinese, Spanish, Arabic, German, Italian, French, Japanese, Malay, Urdu, and Romanian languages along with English [34]–[36]. For example, Babelsenticnet [37] is a concept level knowledgebase for multilingual sentiment analysis that provides support for more than forty languages including Hindi/Urdu. Similarly, in [38], authors build a multilingual sentiment classifier on the Malaysian social media disaster dataset to find the sentiment conveyed in Malay and English languages.

In the South Asia region, most people are unable to speak or even understand English. Consequently, the majority of people prefer to type reviews in Urdu. However, they do not have enough skills to type in Urdu directly. Thus, they switch to Roman Urdu for expressing their sentiments on social media or e-commerce sites. As discussed earlier, Babelsenticnet provides support for Urdu/Hindi languages. However, it does not support Roman Urdu as it is a poor resource language. Therefore, in this paper, we have analyzed social media dataset containing multilingual reviews of users in Roman Urdu and English to extract their true sentiments using unsupervised machine learning techniques.

E. RIDE SHARING PLATFORMS

The ridesharing service is a transportation network that provides a platform to connect drivers having private automobiles and customers looking for a taxi. There are many issues in these platforms (e.g., Uber, Careem, Ola, Taxi, Blacklane, Talixo, and Lyft) regarding the QoS as mentioned in [39]. For example, Shokoohyar [40] investigates the ride sharing platforms from driver's perspective by using online reviews of drivers to compare Lyft and Uber. The results conclude that Uber is slightly better than Lyft in terms of driver's job perspective. Saragih and Girsang [41] compare prominent ride sharing platforms in Indonesia and discuss the feedback of users about these platforms. Similarly, Baj-Rogowska [17] classifies customer opinions about Uber services as positive, negative, and neutral by using customer reviews posted in the English language. The author performs sentence-level sentiment analysis and results are generalized by considering the Uber service as a whole.

Comparing with the above work, this paper deals with the reviews available in both Roman Urdu/Hindi and English languages in India-Pakistan region considering all important aspects of the service. The reviews are extracted from third party online social network site (i.e., Facebook) to maintain their transparency. In Roman Urdu/Hindi, a customer uses Roman alphabets to express their sentiments in a free and open manner. Therefore, it is important to analyze these Roman Urdu/Hindi along with English comments to depict the actual sentiments of the customers about the service in this region.

III. METHODOLOGY

This work is centered on aspect based sentiment analysis of customer reviews for Kansei engineering of Uber service. The snapshot of the proposed methodology is illustrated in Figure 1. In this work, we have selected Uber as a target service. Next, we have collected the online customer reviews expressing their sentiments about the service in Roman Urdu/Hindi and English languages. In the next step, Roman Urdu/Hindi comments are translated into the English language. After pre-processing, aspect based sentiment analysis is carried out on most frequent features along with nouns and adjectives to extract prominent aspects of the service. Finally, customers' sentiments are clustered into these aspects based on their polarities using unsupervised machine learning technique to perform Kansei engineering of the service.

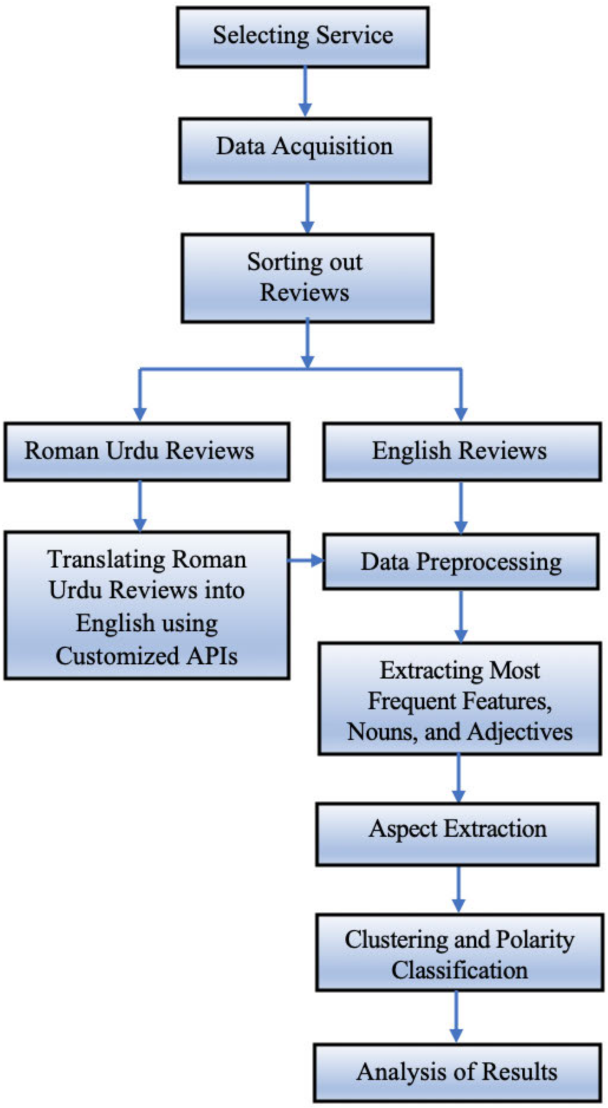


FIGURE 1. Proposed methodology - Aspect based sentiment analysis of ridesharing platform reviews for Kansei engineering.

A. TARGET SERVICE - UBER

In this work, we have selected Uber as a target service. It is operational in 85 countries comprising of almost 785 metropolitan areas with over 110 million active users. Besides ridesharing, Uber is also offering other services to its customers such as food delivery, electric bicycle-sharing system, etc. Uber started his business in India and Pakistan since 2013 and 2016, receptively. At present, the service is operational in more than 50 metropolitan areas of the region. The service is a highly popular mode of transport in the region as most of the people in these countries do not have their own vehicle. A huge amount of customer reviews are available online about the performance of the service, which can serve as an input for Kansei engineering after sentiment analysis.

B. DATA ACQUISITION

Facebook is an excellent platform to collect customer reviews about any service as it has more than 2.5 billion monthly active users. It provides a neutral platform for the customers to post their sentiments freely without any biasedness. Further, companies have no right to change them for their business purposes. Therefore, the Uber Facebook page is selected to collect the customer reviews with the help of a web crawler (i.e., Facepager available at https://github.com/strohne/Facepager/releases) instead of Uber's own app/web page. The reviews are saved directly into the CSV file. Each review has a unique userID, postID, date, time, and review text. After filtering, the resulting file contains 3853 reviews in Roman Urdu and English languages collectively.

C. SORTING OUT COMMENTS

This step separates Roman Urdu and English reviews in two different files. Roman Urdu reviews are translated into the English language to get all reviews in one language and make them ready for the next pre-processing step. Customized APIs are used to translate these reviews into English. The example of converting Roman Urdu review into the English language is shown in Table 1.

D. DATA PRE-PROCESSING

The sorted reviews are in an unstructured form therefore, data pre-processing is carried out in five different steps. These steps include Tokenization, Parts of Speech (POS) tagging, Removal of stop words, Stemming & Lemmatization, and Vectorization. Each step is elaborated with the target review text in Table 2.

TABLE 1. Example - conversion of roman urdu review into english.

Review text in Roman Urdu	Text translated into English
"mujhe us ride pe charge kia gea jo mei nai kabhi li hi nahi. Aap se contact krney ki bohat koshish ki. Lekin nahi kr saki mei dobara kabhi uber use ya promote nahi krun gi "	"I was charged for a ride that I never took. have tried again and again to contact you. but can't I will never use or promote uber again"

TABLE 2. Data pre-processing of review text.

Pre-processing steps	Output
Example review text	"I was charged for a ride I never took. have tried again and again to contact you. but can't I will never use or promote uber again"
1. Sentence segmentation	['I was charged for a ride I never took.', 'have tried again and again to contact you.', 'but can't I will never use or promote uber again']
2. Word segmentation	['I', 'was', 'charged', 'for', 'a', 'ride', 'I', 'never', 'took', 'have', 'tried', 'again', 'and', 'again', 'to', 'contact', 'you', 'but', 'can't', 'I', 'will', 'never', 'use', 'or', 'promote', 'uber', 'again']
3. POS tagging	[('I', 'PRP'), ('was', 'VBD'), ('charged', 'VBN'), ('for', 'IN'), ('a','DT'), **('ride', 'NN')**, ('I', 'PRP'), ('never', 'RB'), ('took', 'VBD'), ('have', 'VB'), ('tried', 'VBN'), ('again', 'RB') ('and', 'CC'), ('again', 'RB'), ('to', 'TO'), ('contact', 'VB'), ('you', 'PRP'), ('but', 'CC'), ('can't', 'JJ'), ('I', 'PRP'), ('will', 'MD'), ('never', 'RB'), **('use', 'VB')**, ('or', 'CC'), ('promote', 'VB'), ('uber', 'NN'), ('again', 'RB')]
4. Removal of stop words	[('charged', 'VBN'), ('ride', 'NN'), ('never', 'RB'), ('took', 'VBD'), ('tried', 'VBN'), ('again', 'RB'), ('again', 'RB'), ('contact', 'VB'), ('cant', 'JJ'), ('never', 'RB'), ('use', 'VB'), ('promote', 'VB'), ('uber', 'NN'), ('again', 'RB')]

1) Tokenization: This process breaks down a text sequence into different smaller pieces such as word, phrase, symbol, etc. based on the grammar of the language. For this purpose, first of all, sentence segmentation is used to divide every customer's review into individual sentences. The punctuation marks such as period and comma are used as a marker of the sentence. Afterward, in word segmentation, the sentences are divided into words and phrases where space is used as an indicator of the next word in a sentence. These small pieces are called tokens. Python NLP package and Natural Language Toolkit (NLTK) [42] are used to carry out tokenization in this work. The example of the sentence and word segmentation are shown in row 1 and 2 of Table 2.
2) Parts of Speech (POS) Tagging: In this process, part of speech tag is assigned to each word in the text. Python NLTK package is used for this purpose. It uses different combinations of letters for each part of speech. For example, 'NN' is a tag used to represent noun, 'RB' for an adverb, 'VB' for a verb, and 'JJ' for an adjective. The example of POS tagging on review text is shown in row 3 of Table 2. For example, 'ride' is a noun, therefore, 'NN' is assigned to it. Likewise, 'VB' is attached to the word 'use' to represent it as a verb. In this way, all the words obtained after tokenization are assigned with respective POS tags. This tagging is an important step of the data pre-processing phase, as a result, the required features are identified and extracted easily.
3) Removal of Stop words: The English language sentences contain an extensive portion of stop words that have little or no value in text mining and natural language processing. Removal of stop words is the process, which is used to eliminate the inappropriate words in the reviews i.e., is, am, are, including different punctuation marks. The objective of this work is to extract the most frequent features from the reviews, however, stop words always have a high frequency in any type of textual data. Therefore, it is extremely important to remove these stop words before performing any analysis on the text. This process reduces the size of the review text to a great extent as shown in row 4 of Table 2. Python Scikit Learn (SKLEARN) and NLTK libraries provide built-in lists of stop words for 16 different languages. The English stop words built-in list provided by SKLEARN is used to eliminate the frequently used stop words from the review text. Moreover, some custom words are also included in the built-in list to remove them while extracting the most frequent features from the text.
4) Stemming & Lemmatization: It is the process of generating root words from different modified forms. The process of stemming truncates the suffix or prefix of the word without considering its meaning. For example, it extracts 'driv' from 'driving' which is not a real word. However, in lemmatization, lemma will be an actual language word as it considers the morphology of the word. For example, it generates the word 'drive' from 'driving', 'drives', or 'drove'. The purpose of this step

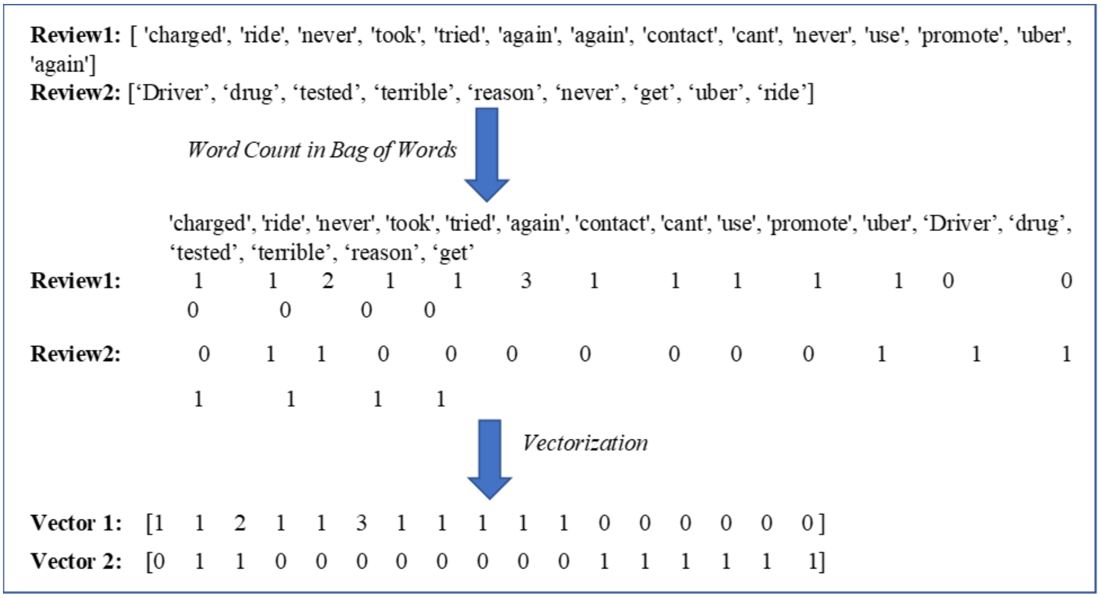


FIGURE 2. Vectorization of reviews.

is to reduce the volume of the vocabulary set generated after pre-processing of the reviews.

5) Vectorization: The pre-processed reviews as obtained through previous steps, are in an unstructured form. Therefore, it is required to convert them into structured data, which is known as a bag of words model (BoW) or vector space model. The BoW is simply a bag of words containing the review text without considering its grammar and sequence. For this purpose, a dictionary is established that consists of all the words present in Review 1 and Review 2 as shown in Figure 2. Afterward, each review becomes a fixed-length vector with dimension equal to the size of the dictionary. The value of each word in the vector is filled with the frequency of that word in the review text as shown by Vector 1 and Vector 2 in Figure 2. The CountVectorizer package of scikit-learn library is used for the said vectorization process [43].

E. EXTRACTION OF MOST FREQUENT FEATURES, NOUNS, AND ADJECTIVES

After pre-processing, the most frequent features are extracted from the reviews using SKLEARN CountVectorizer, Collection, and RE packages of the Python. We extracted more than a hundred features from the reviews. However, after sorting and filtering, the total features are reduced to fifty as shown in Figure 3. The descriptive statistics reveal that 'Driver', 'Company', 'Service', and 'Ride' have the highest frequency in the data. In order to get comprehensive sentiments about the service, most frequent nouns, and adjectives are also mined separately form the reviews and are summarized in Figure 4 and Figure 5. We found that the highest frequent features like 'Driver', 'Company', 'Service', and 'Ride' are almost the same as nouns with the highest frequency. Afterward, the extraction of most frequent adjectives demonstrates that 'New', 'Late', 'Wrong', 'Disappoint', and 'Fraudulent' adjectives have the highest frequency as compared to others.

F. ASPECT EXTRACTION

Aspects are those words that are frequently used by the customers to express their sentiments about the service, thus, representing their significance. These aspects are actually concealed in the reviews since customers do not specify them clearly in the reviews. Therefore, the highest frequency features from the most frequent feature list are taken as aspects of the service i.e., 'Driver', 'Company', 'Service', and 'Ride'. Similar aspects have been revealed when we parsed the most frequent nouns, which denote their prominence for Kansei engineering of the service. Thereafter, customer sentiments are clustered based on these aspects using a Probabilistic Latent Semantic Analysis (PLSA) [44] as explained in the next section.

G. CLUSTERING AND POLARITY CLASSIFICATION

The clustering is done by applying the PLSA using Matrix Factorization Model. As a result, we get four clusters containing the most frequent words used by the customers. Each cluster has aspect word as a top word with the highest frequency i.e., 'Driver', 'Company', 'Service', or 'Ride'. It confirms that these highest frequency words are the main aspects of the Uber service. The snippet of clustering is shown in Table 3.

Next, we use a lexicon-based approach using SentiWordNet [45] for the polarity classification of the sentiments used

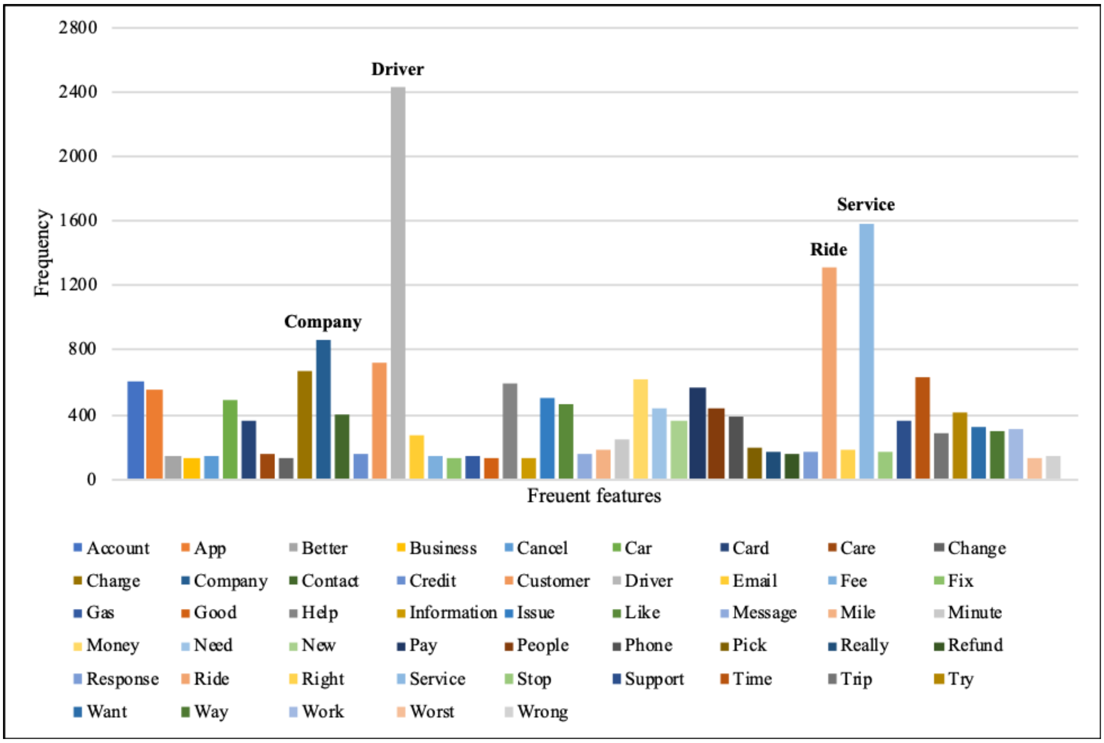


FIGURE 3. Most frequent features from reviews.

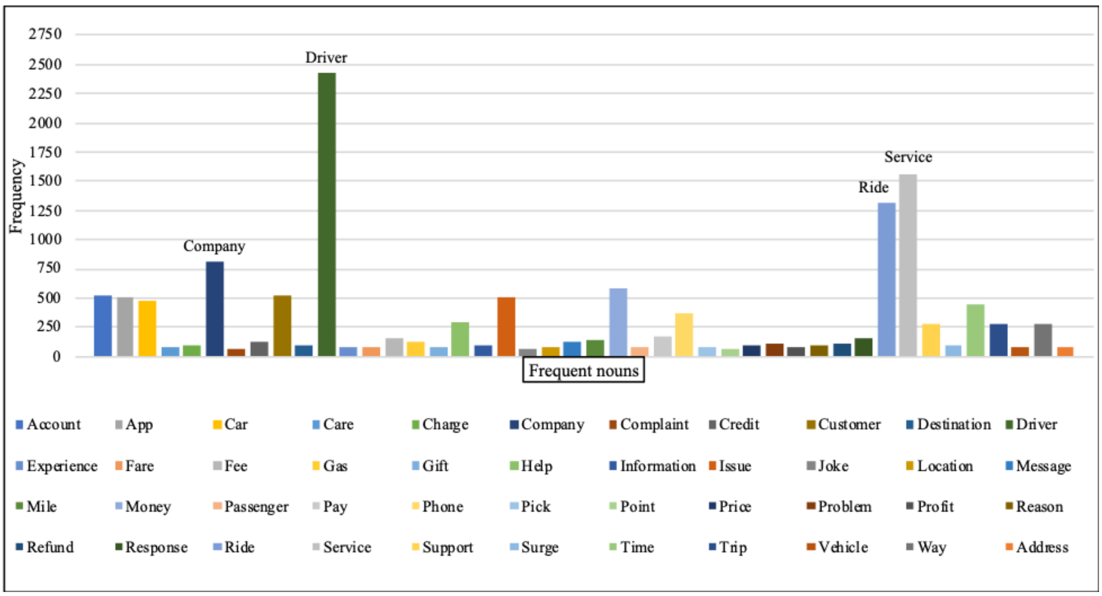


FIGURE 4. Most frequent nouns from reviews.

by the customers. In this process, each aspect with its opinion words are passed to SentiWordNet as a key value pair e.g., (service, good), (ride, complaint), (driver, disappoint). Afterward, SentiWordNet retrieves the opinion from this key value pair and calculates its polarity. Based on the calculated polarity, each opinion word is regarded as positive or negative.

IV. RESULTS AND DISCUSSION

A. FREQUENCY ANALYSIS OF MOST FREQUENT FEATURES, NOUNS, AND ADJECTIVES

The extraction of most frequent features revealed that the word 'Driver' was the most discussed feature (with the highest frequency of 2428) in the reviews. Similarly, the other highly discussed features are 'Service', 'Ride', and

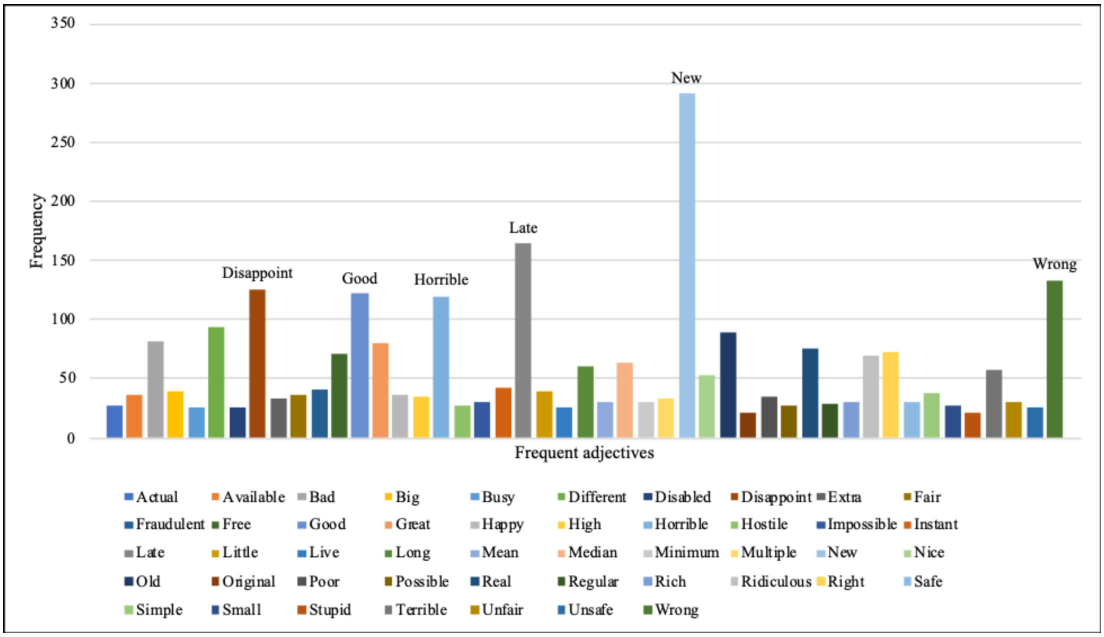
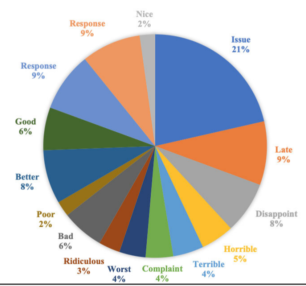


FIGURE 5. Most frequent adjectives from reviews.

TABLE 3. Snippet of clustering generated using PLSA.

Cluster # 1	Cluster # 2	Cluster # 3	Cluster # 4
driver	company	service	ride
issue	issue	issue	charge
late	bad	helpless	issue
better	good	like	refund
disappoint	worst	bad	complaint

TABLE 4. Frequency chart of Driver's cluster.

Frequency of review words		Driver's Cluster
Positive	Negative	
Better (88) Good (70) New (163) Response (97) Nice (25)	Issue (242) Late (104) Disappoint (85) Horrible (54) Terrible (50) Complaint (45) Worst (43) Ridiculous (35) Bad (69) Poor (25)	

'Company' as shown in Figure 3. In the case of most frequent nouns, the same features ('Driver', 'Company', 'Service', and 'Ride') have the highest frequency as shown in Figure 4. As a result, these four features and nouns collectively become the prominent aspects of the service. In terms of adjectives, most repeated ones are 'New', 'Late', 'Wrong', 'Disappoint', 'Horrible', and 'Good' as shown in Figure 5. These most frequent aspects and adjectives define the relationship between service providers i.e., Uber and customer demands. This relationship is an aid for Kansei engineering of Uber to fine-tune their services according to the intentions of the customers.

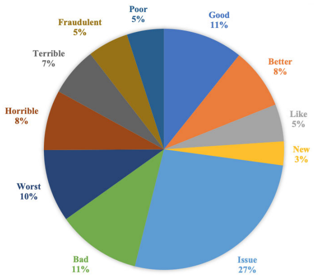
B. FREQUENCY ANALYSIS OF CLUSTERS

In order to mine hidden sentiments about the service, customer sentiments are clustered based on each prominent aspect of the service (i.e., 'Driver', 'Company', 'Service', and 'Ride'). Additionally, the polarity classification of sentiments in each cluster is carried out. It helps to reveal the customer feedback about the service in a true sense. This feedback serves as an input for Kansei engineering of the service.

In this work, the Driver's aspect constitutes a biggest cluster containing maximum number of features with highest frequency as shown in Table 4. In this cluster, the customers discussed Driver's aspect using nouns and adjectives like 'Issue', 'Late', 'Disappoint', 'Terrible', 'Horrible', 'Worst', 'Ridiculous', 'Bad' and 'Poor' to express their negative sentiments about the service. Similarly, they used adjective like 'Better' and 'Good' to express positive feedback about the service. However, the frequency of negative sentiment is much higher as compared to the positive one. The higher frequency of negative sentiments conclude that customers are not satisfied with the behavior of the 'Driver'. Therefore, it is an important result for Kansei engineering of the Uber service to tame their drivers according to expectations of the customers.

The next cluster is about the aspect 'Company' (i.e., Uber). It forms the second highest frequency cluster and is shown in Table 5. In this cluster, customers used words like 'Issue', 'Bad', 'Worst', 'Terrible', 'Horrible', 'Fraudulent' and 'Poor' to show their dissatisfaction towards the service. On the other

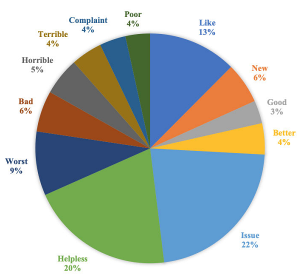
TABLE 5. Frequency chart of Company's cluster.

Frequency of review words		Company's Cluster
Positive	Negative	
Good (84) Better (64) Like (39) New (25)	Issue (209) Bad (88) Worst (76) Horrible (63) Terrible (51) Fraudulent (43) Poor (39)	

hand, they used 'Good', 'Better', 'like' and 'New' to express their positive sentiments about the Company. The frequency of negative words used in this cluster is less as compared to Driver's cluster, which shows that customers have an optimistic behavior towards the Company.

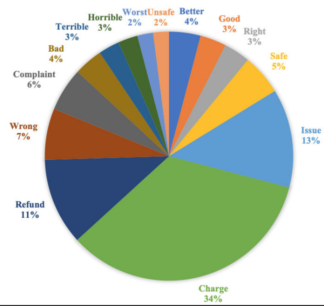
The third cluster represents the 'Service' aspect of the Uber as shown in Table 6. Again, the customers mostly used negative words like 'Issue', 'Helpless', 'Worst', 'Bad', 'Terrible', 'Horrible', etc. while used positive words 'Like', 'New', 'Good' and 'Better' to express their sentiments about the Uber service. Finally, in the fourth cluster, aspect 'Ride' is evaluated and results are summarized in Table 7. The cluster is also dominant with negative sentiments showing customers bad experience about the 'Ride' aspect. The frequency of negative words used in this cluster concludes that customers are highly concerned about the 'Ride' aspect of the service after driver's behavior.

TABLE 6. Frequency chart of service cluster.

Frequency of review words used		Service Cluster
Positive	Negative	
Like (54) New (25) Good (14) Better (19)	Issue (96) Helpless (88) Worst (39) Bad (25) Horrible (23) Terrible (19) Complaint (16) Poor (15)	

In summary, the negative words like 'Issue', 'Terrible', 'Horrible', 'Bad', and 'Worst' are present in all clusters with moderate to high frequency. However, the positive words like 'Good' and 'Better' have low to moderate frequency. These findings indicate that the customers are mostly complaining about different aspects of the Uber service. In order to improve the service, Uber can incorporate this aspect based sentiment analysis in their Kansei engineering strategy to uplift their business in the region.

TABLE 7. Frequency chart of ride cluster.

Frequency of review words		Service Cluster
Positive	Negative	
Better (24) Good (20) Right (20) Safe (31)	Charge (200) Issue (75) Refund (66) Wrong (39) Complaint (33) Bad (22) Terrible (16) Horrible (15) Worst (12) Unsafe (12)	

V. CONCLUSION AND FUTURE WORK

The purpose of this work is to perform aspect based sentiment analysis to extract the customer sentiments for Kansei engineering of the Uber service in the India-Pakistan region. For this purpose, online reviews are collected from the Facebook page of Uber service where users post their sentiments openly without any bias. As the major portion of these reviews is in Roman Urdu/Hindi, therefore, they are translated into English using customized APIs. Afterward, aspect based sentiment analysis is carried out on most frequent features, nouns, and adjectives to get prominent aspects of the service i.e., 'Driver', 'Company', 'Service', and 'Ride'. Further, positive and negative sentiments of the customers are clustered for every aspect of the service. This revealed that the majority of the customers are complaining about the service and they are highly concerned about the 'Driver' and the 'Ride' aspect of the service. Thus, Uber can integrate this aspect based sentiment analysis in its Kansei engineering process to enhance its business in the region.

As Roman Urdu is a poor resource language and does not contain a standardized dictionary. The spellings of a word vary greatly from person to person or even the same person uses different spellings on different occasions. Therefore, in this work lexicon-based approaches with base machine learning models are giving quite satisfactory results. However, for a huge amount of Roman Urdu reviews that contain different spellings for the same word, deep learning models can be used in the future to provide fine-tuned analysis.

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