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RESEARCH ARTICLE

Opinion Mining from Online Travel Reviews: An Exploratory Investigation on Pakistan Major Online Travel Services Using Natural Language Processing

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ABSTRACT Online tourism evaluations are a valuable origin of data for traveler organizations, defining as they could be excellently recognized critically prompting traveler opinion-designing using opinion mining. As technology advanced, online review forums of any organization become an attractive source of communication with them, where people can share their views in the form of comments. The main determination of this research article is to recognize normal topics and connect them to contrasts in web-based travel reviews. Online millions of reviews, got from two significant web-based travel organizations (Uber, and Careem) in Pakistan, and a semantic affiliation examination was utilized to extract thematic words and construct a semantic affiliation organization. In the Python programming language, we use natural language processing (NLP), which includes data cleansing and tokenization. The results of network visualization are able to evidently recognize main topics and thematic words with social network associations. The proposed logical system extends our grip on the strategic complications and gives new points of view on the best way to dig popular assessments to assist vacationers, inns, and travel industry organizations.

INDEX TERMS Opinion mining, online travel reviews, social network association, thematic words, natural language processing, sentiment analysis.

I. INTRODUCTION

Internet is a source that provides a variety of information with different benefits for travelers irrespective of the time of their journey, whether they are during a tour, planning a tour, or ending a tour [1]. User-generated content (UGC) is one of the most recent databases of information for travelers. This platform offers you to keep an eye on the comments, profiles, and pictures that are posted by travelers during their tours or what experiences they have shared [2]. UGC helps a traveler to post his reviews and experiences on travel-related websites and other generic social media platforms or social networking sites. This content is used to highlight a traveler's feedback about the experience he or she had about a certain destination or travel product. As there is a lot of ambiguity involved in the hospitality industry and travel products, so, travelers usually rely on the UGC already available on the internet which is generated by different travelers and take their bits of advice and recommendation about planning certain trips to the destination

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where they don't have any previous visits or the high-risk destinations [3].

Online user reviews, like online traveling reviews from customers, takes become extensively working in the traveler and cordiality ventures because of the quick development of Web innovations. Tourists are more likely to share their vacation experiences on websites like Trip Advisor [4] such dynamic client-shared records of explorers' encounters have for some time been viewed as a common place kind of online travel survey. Now determination of using websites has changed from reading to writing [5]. Now a day's online reviews have become popular. Organizations take those online recommendations and reviews very seriously as they consider this as a reference for customers to make purchasing decisions [6]. These online opinions and reviews provide problem-solving information when extracted and analyzed according to the issues one is facing [7].

The rise in social media, increase in user-generated content and their effect on the world were a revolution in the past decade. This Electronic word-of-mouth information (eWoM) contributed a lot to revolutionizing the marketing industry. As with UGC, in the travel and hospital industry, the term Traveler-generated content (TGC) is used to share content related to the travel and hospital industry. Online travel reviews and ratings along with travel blogs and vlogs have now become a useful and prominent source of gathering information for travelers. Different traveling-related websites collect the experience and comments of travelers about the products, activities, attractions, places, services, and products to measure satisfaction levels and this information is then used by the travel planners to plan their journeys [8].

Consumers post their experiences, reviews, pictures, and other information which these travel websites allow them to post. These online reviews help travelers to remain informed better than ever. But sometimes, due to excessive information available on the internet, users get overwhelmed and confused about what information is useful for them or which to take into consideration and guidance [9]. This load of information also forced website owners and developers to organize the information and make their designs better. The study focusing on qunar.com, a leading Chinese travel website, it was investigated how the design of the website impacts the rating behavior of travelers and the ways which are used to manage those reviews [10].

According to [1] the effectiveness of online consumer reviews/feedback by examining basic two features of online material: a). The individualities of review providers, such as the revelation of personal identity, the customer's skill and repute, and b). Feedback/ reviews themselves include quantitative (i.e. star condition and size of feedback) and qualitative measures (i.e., assumed enjoyment and review adaptability) [11]. It is not an easy task to perform sentiment analysis of these online reviews in case of natural language processing. These reviews are basically the sentiments, feelings, views, or thoughts of the people described in the form of text and they can be positive, negative, or neutral as well.

Before tourists take a decision, consumer reviews and feedback are easily influenced by others' perceptions, and their desire to seek out peer consumer opinions and experiences is relevant [4], [12], [13], and [14]. According to business statistics, over 77 percent of potential travelers will ''always'' or ''usually'' wait until they read internet assessments before making a decision [15]. Travelers can minimize their perceived uncertainty and get indirect purchase know-how by exploring knowledge nodes (e.g., traveling websites of companies, and online traveling reviews), resulting in pleasant psychosomatic knowledge [6], [16]. Consumers' online reviews are very beneficial because they are more suitable in their hunt for information, but they also incur higher intellectual costs. When gone up against an enormous number of web assessments, purchasers can become puzzled and lost, bringing about helpless independent direction and theoretical tension [6]

Online review quality and customer attitudes toward review information are influenced by the tourism organization [12]. The size, community qualities, readability, correctness of knowledge, received data, and verbal stylishness of reviews are the primary aspects that influence information acquisition excellence [17].

In Fig 1, items with positive and negative feedback with some remarks of nonverbal importance were separated to eliminate the unwanted information during the information mining [6]. Words were the main portion that was used to highlight items while some portions of things were also included in items. The language in reviews which is difficult to read seldom gets the attention of the consumers [17], and this has an impact on the competitiveness of the traveler companies. (E.g., reputation and profits).

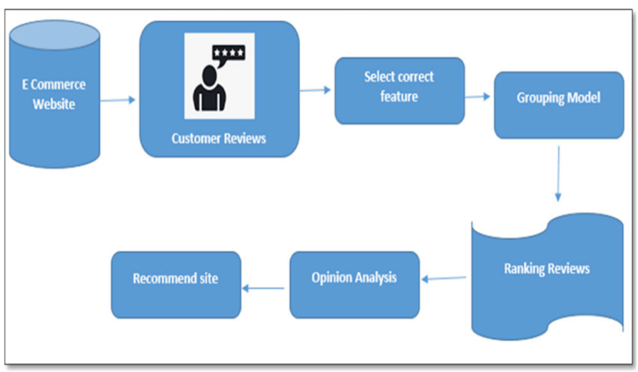

FIGURE 1. Opinion mining process.

Consumer attitudes about traveling using the information they get from online reviews are influenced by the quality of online review information [13]. The size, community qualities, readability, the correctness of knowledge, received data, and verbal stylishness of reviews are the primary aspects that influence information acquisition excellence [18], [21]. Consumers will indicate reduced reservation intention if online reviews are difficult to read, according to [17], which affects tourist businesses' competitiveness (e.g., for example, repute and profits).

As a result, in the sphere of practice and academics, promptly getting first-rate facts from a large number of data taken from online reviews has become a significant problem. Poll reviews [19], numerical models [20], measurable examination [19], [21]. Grounded hypotheses have all been utilized in past investigations on internet-based travel assessments [17], [22]. Text-based online evaluations frequently contain vast data sources that have the logical competencies of cultural econometric and statistical methodologies [23]. Within the review data, finding statistically significant differences between different sorts of groups is tough [24], [25].

Semantic association exploration can swiftly excerpt significant subject words from a huge number of texts. In the present-day world of technology, the number of online travel agents (OTA) is growing day by day [22]. People use to get benefits of these technological advancements to get themselves prepared more quickly with ease.

Online traveler companies want to achieve success in business, and association analysis at a semantic level by exploiting the rich idea tree structure and semantic information supplied [24], [25]. Customary text examination innovations, (for example, fluffy area cosmology, and backing vector machine) are less trustworthy, and the examination results have less reference worth and materialness [24].

Semantic association network helps tourism associations to change the disparity in terms of distribution of thematic word contents, organizational plot, and communal connections [26]. The main purpose is to calculate the frequency of main keywords from the dataset [18]. The Jieba toolkit was used for this purpose, it selects the thematic words and removes the irrelevant or redundant reviews from the dataset. Jieba toolkit for Chinese word segmentation in the python language was introduced [26]. For manual mining, this method was substantially used. Furthermore, for the calculation of thematic words' frequentness, the NLTK was used. The formula used for this purpose is shown as (1):

$$\mathrm{Fi} = \mathrm{Ri}\ \mathrm{X}(\mathrm{Li}/\mathrm{Lt}) \quad (1)$$

Here Fi represents the occurrence of the thematic word i, Ri is the number of reviews that occur in datasets, Li is the size of i, and Lt is the size of review words.

Thematic words can impart knowledge and information about a particular subject [27]. Thematic words are illustrated in Fig 2 and their graphical reprsentation is presented in Fig 3 represent a word that expresses some knowledge. The features of shortness and timeliness as well as a great amount of information. An analysis of thematic word objectives is to eliminate worthless words. So the thematic words play a vital role to affect research outcomes of the thematic extracted words from the datasets of online reviews through the data preprocessing [26]. In internet-based travel assessments, the semantic linkage of two archives is regularly determined by demanding emphasis just as by the significant reasoning behind the issue. In the investigation of online travel assessments, a blend of semantic thought and affiliation examination techniques can decrease test predisposition and refine the perception granularity of subject recognizable proof to the word quantity.

As a consequence, precisely taking out the thematic words and the association words, can considerably increase the effectiveness and excellence of online travel reviews analysis. Moreover, it can achieve esteem added from data to information to insight [18]. Given this, the conclusions inside internet-based travel surveys on the three stages by utilizing semantic affiliation investigation, giving functional assistance to understanding sightseers' conduct and prompting upgrades in the travel industry business promoting. In particular, the primary point of this review is to respond to the accompanying inquiries:

(1) What subjects are talked about in internet-based travel audits?

(2) Know how bigrams of co-event expressions of semantic affiliation are developed?

(3) What are the underlying properties of semantic affiliation organizations?

(4) How would we be able to distinguish the focal point of a conversation by picturing semantic affiliation organizations?

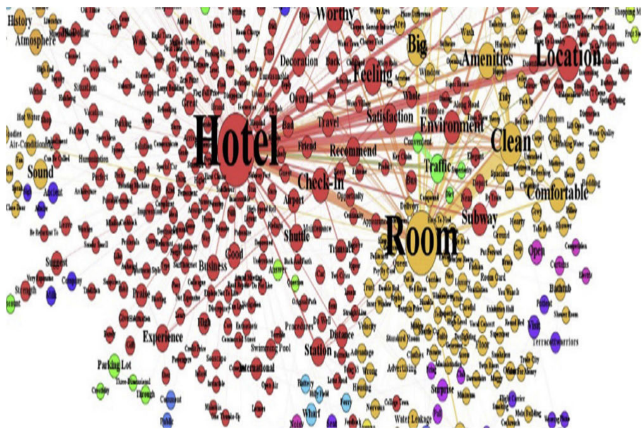

FIGURE 2. Network Picturing of thematic words.

Research Contributions: This research work helps online traveling companies maintain their work quality by using their online reviews which are sent by their riders. The contribution of this research is as follows.

1. Suggested an effective method of identifying travel-related issues.

2. The proposed model will find problems in traveling (wrinkling) to produce better facilities with the help of user reviews.

3. The proposed model will help determine the reason for the problem and investigate the level of commitment and effort required to resolve the problem.

4. To develop a model that defines how to address what would be most effective, and after making changes, consider potential impacts.

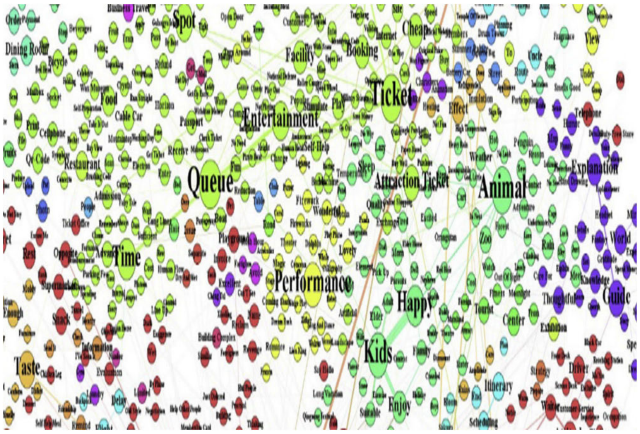

FIGURE 3. Graphical representation of thematic words.

The remains of this research work are structured as Section II presents background knowledge of research work that is related to online reviews, and opinions are taken out from online reviews. Section III delivers a literature review related to online reviews. Section IV delivers a proposed methodology explanation of our research work, how to collect data, and precise that data. Section V delivers outcomes of data obtained after applying research methodology, including statistical analysis of thematic words, and the construction of bigrams of the co-occurrence of semantic association. Section 6 presents the discussion and limitations. Section 7 presents conclusions and future guidelines.

II. LITERATURE REVIEW

The literature related to online travel reviews and opinion mining has been conferred in this section.

A. ONLINE TRAVEL REVIEWS

Online reviews and feedback are posted by consumers who have planned their decision, and they incorporate customers' hassles, assessments, and sentiments [28]. Online reviews are a channel for getting decision data as well as the reason for settling on the trip assiduity choices. The passions communicated by judges on particulars or administrations impact other guests' steal things [26]. For undertakings and merchandisers, the highlights of online reviews, similar to comprehensiveness [29], professionalism [30], quality [31], and character [32], basically affect item deals [33].

The exploration of online reviews of customers contributes an influential encouraging tool [34] and supporters recognize the significance of word of mouth, particularly with honor to its relations for trust and connected outcomes. Rider's gratification is the outcome of a rider's opinion of the services that the company provided to them. Sentiment analysis using deep learning applied to tweets was found in [35] and [36]. The methodology to use deep learning models to increase the authenticity and accuracy of sentiment analysis was described by the authors.

For understanding the preference of consumers and consumer demand, customer reviews have become a major source of attaining information for researchers and practitioners. This can include understanding or predicting the financial outcomes of an activity or attempting to boost sales [37]. Online reviews help consumers in overcoming inaccurate service or product descriptions. With the help of these online reviews, the consumers can rely on the first-hand experience of customers who already used that product or service as some products like vehicles, etc. are high-involvement products. As these online reviews have now become a source of attracting customers so many firms encourage their customers to post their experiences and feedback about their products and services online. Many companies also offer different kinds of vouchers or benefits for such people who post about them on social media.

According to [38] for decision making online reviews are taking importance. Most customers read the reviews before making online orders which indicates that online response plays a vital role in the success of any company. Companies also acknowledge the importance of online responses sent by their customers and use that reviews to enhance their product quality. Novel framework use to categorize the large number of reviews into changed divergences.

Electronic word of mouth (eWOM) to explore the role word of mouth plays when it comes to online review generation and utilization of these reviews. The consumption process is also a beneficiary of the eWOM. Researchers examine the impact of eWOM on the sales of products and how these online reviews are perceived as helpful in the consumption process. For example, the findings [39] suggested that sales are positively impacted by the number of consumer reviews posted and sales are not associated with the ratings of these online reviews. Previous studies focused on a number of reviews posted as a proxy for understanding the sales levels of hotels as several reviews posted have a positive impact on product sales.

Nowadays social media has become a part of our life. Most people travel online using online services which different agencies provide to their customers. Reference [40] Empirical Analysis is used to explore the role of the social interface network system (SNIS) like Facebook in review generation on OTAs. Online travel reviews reflect the standing and contentment of the travel agencies.

At present, the use of online channels is extending. Customers gave their reviews according to services that they got from agencies. In [41] NLP is used for sentiment analysis. Feelings are analyzed to make them suitable for objectivity in consumer research with keeping their focus on travelers by studying their emotions and feelings.

Contrasting other rider goods, travel acceptance needs more than a humble acquiring conclusion, and traveler ingestion is strong-minded by public preparedness. Online travel studies are rich, difficult heaps of facts that mirror travelers' come across and valuations of items which are important wellsprings of data for travelers to work with the formation of drive courses of action [42].

Online travel assessments, which reflect the standing and contentment of the travel company objections, are an important piece of the travel industry's objective organization image and forthrightly affect sightseers' seeming quality, contentment, and social aim [16], struggled that bargain hunter can get a natural impression of the travel industry protestations by examining other travelers' internet founded travel surveys, supplementary them with lessening hazard defenselessness and successfully make travel preparations. Although online travel assessments give somewhere to live buyers' movement choices, huge audits have likewise intensified dismay concerning data over-burden in the great information era. Eliminating central issues from online printed assessments is mind-boggling and checking, yet it is essential for expecting, interpreting, and responding to client conduct [26].

The concept of "Destination Image" can be used both theoretically and practically to get insight into how tourists view a specific location. According to [43], the primary methods, representations, measurements, and conclusions obtained from a computational science stance in relation to destination image in tourism studies were all identified. They found two distinct taxonomies: one for the overall set of approaches, and another for the outcomes that could be expected from using those approaches. Based on their findings, they concluded that while electronic information is growing in importance, surveys are still the most trusted primary source. Nonetheless, word frequency-based methods remained the most popular for information analysis until recently, when neural networks and deep learning methods began to replace them.

The explosion of Web 2.0 and user-generated content means that DMOs no longer have a monopoly on the information that tourists use to form their impressions of a destination. Through language recognition, frequency analysis, and term categorization of more than 150,000 online travel reviews written in English, Spanish, French, German, or Italian, Marine-Roig and Huertas [44] examined the effects of the terrorist attack in August 2017 and the Catalan sovereignty process, which took place during the last quarter of 2017, on the online destination image perceived and transmitted by tourists. Despite the intensity of both tragedies and the extensive coverage they received in the international media, the results demonstrated that tourists felt comfortable going about their normal activities. Businesses can benefit from hearing customer feedback in the form of online reviews to enhance product and service delivery.

B. OPINION MINING OF ONLINE TRAVEL REVIEWS: PRELIMINARIES

Opinion mining is an innovation that consequently separates online remark data by utilizing text-based investigation, including coding and regular language handling. It investigates individuals' perspectives, examinations, mentalities, and feelings towards associations, substances, individuals, issues, activities, points, and their traits [42]. The methodology extricates the text data from item review by highlighting development innovation, (for example, the sack of words) and uses an order strategy to break down internet-based audits [45]. Inside the web-based travel survey setting, the proposed assessment mining technique enjoys critical benefits of OK precision and asset reserve funds in managing unstructured audit texts [4], [26] analyzed millions of online reviews taken from their traveling websites to recognize the main interest of traveler requirements based on Inactive Dirichlet Analysis(IDA) opinion extraction approaches and exposed well-regulated scopes that are key for traveler's organization to manage their interaction with their riders. Over the past decade, a huge interest in sentiment analysis which is an application for natural language processing is observed [46]. Different terms used to describe sentiment analysis in the literature include mood extraction, emotion analysis, and opinion mining.

Data mining or the discovery of knowledge using different textual databases is termed Text mining. This term refers to the process to extract non-trivial patterns and interesting information from unstructured databases of text documents [47]. Text mining is not confined to market surveys only. It helps you in diverse context studies including tourism, medicines, or even customer relationships management, etc. Much applied previous research also included text mining. With the tourism and hospital industry in focus, many studies were performed in the field of hospitality and tourism industry which included text mining.

Opinion mining is another technique used to extract information from unstructured textual information. It helps to analyze the piece of text to form an opinion about a person's attitude. Opinion mining helps to evaluate the positive, negative, or neutral context of opinion attached to a piece of text. The degree of polarity being high, mild, or moderate can also be found through opinion mining. Different opinion reviews from different websites are used to collect the user's opinions, feelings, and attitudes. Opinion mining is a convolutional neural network (CNN) and aspect base ontology method or classification used for sentiment analysis [11].

Researchers nowadays use these online reviews to understand and measure the satisfaction levels of consumers in the hospitality industry. Many recent studies have employed these text-mining techniques to evaluate these online reviews in the hospitality and tourism industry. For example, the service quality of hotels was measured by online reviews through text mining [48]. By employing text mining, they identified different factors which have a significant impact on the satisfaction of customers.

The terminology-based approach group's communication feeling boundary by depending on an opinion word reference and phonetic information approach, which incorporates a corpus-based methodology and a word reference-based methodology. The AI method, which categorized mainly into three types: supervised learning, semi-supervised learning, and unsupervised learning [42].

NLP techniques are used to input text in the first step of processing. Computing and selection which are components of feature engineering are the second and third steps. Document representation is the fourth step. The opinion mining process is the last step to compute the polarity of the selected text.

C. SEMANTIC ASSOCIATION ANALYSIS (SNA)

This is a significant analysis system [26], which was declared in the study of the response of the brain to expected arguments [49]. Common styles include technology that processes natural language, content prototypes, etc. Bigram co-occurrence can help information harm and deformation in verbal evaluation information aggregation and calculation and make the calculus results more accurate [50]. The semantic association is particularly analyzed on exterior information and a semantic relation to construct a model of point arguments, which enables better textbook brackets than that planted in previous studies. This method has been extensively established in consideration relating to the intelligence of business and earthly performance.

Natural Language Processing approaches are applied to remove and evaluate the supreme common phrases used within side the platforms. An Association Rule Learning established of rules is executed, to excerpt desired locations for delightful companies of reviewers, through mining exciting organizations of most of the nations of the foundation of the reviewers and the maximum common locations visited. By elaborating to be had data, it's far more viable to routinely expose precious statistics for riders and travelers. The statistics regularly extracted may be oppressed, for example, to construct a suggested machine for clients or a company's evaluation device for carrier providers. The main Propose of Semantic association analysis is to define the semantics which define by two keywords and calculate their co-occurrence frequency and linked all highly frequently occurred phrases [51].

The semantic web designed by semantic association is a type of demonstration of social networks. Apply opinion mining on online reviews sent by riders and create social network theory. Social network analysis emphasizes that each separate has ties to other individuals (Wasserman & Faust, 1994), and such ties are a means of identifying prospective relationships [52].

Travelers use social networks for both accomplishing information on probable end nodes and for maintaining undesirable judgments, in demand to figure out the main consequences for travelers' companies. Guesthouse reviews, eating place reviews, and desirability reviews are common sources of information for travelers seeking travel info and planning travel arrangements, as well as buying tickets and somewhere to stay online [53].

Using the social network analysis method, exposed that the latitudinal structure of self-service travel in Yunnan region is pigeon-holed by "closely contacting with all others nearby, although the overall connection is moveable". Though, there are still some holes in the research on classifying the latent needs of consumers based on word granularity. This study helps to conduct an SNA of online traveling reviews [54].

Table 1 gives details of different techniques used by researchers for opinion mining on traveler reviews. Most of

TABLE 1. Summary of reviews based on opinion mining.

Ref.	Method	Dataset	Target
[46]	Classification based on lexicon	Twitter, Facebook Instagram, LinkedIn	Reviewing the techniques of opinion mining
[38]	Novel framework	Yelp, Amazon, and Movie's dataset	To categorize the large number of reviews into changed divergences.
[40]	Empirical Analysis	Customers reviews from TripAdvisor.com	Discovers the roles of SNIS in review generation on OTAs
[35]	CNN	Seme Val 2016 workshop	Extraction of behavioral information of user
[36]	CNN, RNN	Twitter	Word embedding according to domain.
[55]	Research framework, as portrayed	Customers reviews from AirBnB.com	Thematic analysis of experiences from review.
[16]	Semiotic based theory	Tuniu, Ctrip	Semiotic, content, and visual analysis used for exploration of image of Huangshan
[41]	NLP	Customers reviews from virtualtourist.com	To analyze travelers' online reviews of Paris.
[11]	Ontologies, CNN, Word2vec	Customers Reviews From booking.com.	CNN, Word2Vec and ontologies as a combination were used as an efficient method for sentiment analysis.
[4]	Latent dirichlet analysis (LDA)	Customers reviews from TripAdvisor.com	Identify the main suggestions of the consumer service by hotel visitor.
[32]	2 × 2 independent experimental research design	OTA (booking center)	Reviewing the effects of online rating about hotel bookings and intentions
[56]	linear mixed model	Customers reviews from booking.com	The target of this study to defining the factors that most significantly effects customer happiness in the hospitality industry
[26]	eWOM	Canadian enrolled student dataset	Comments analysis of Facebook posts over choice of hotels

the researchers used Empirical Analysis, Classification based on the lexicon, convolutional neural network (CNN), recurrent network (RNN), electronic word of mouth (eWOM), latent Dirichlet analysis (LDA), and natural language processing (NLP). The goal of this research is to focus on the reviews of the customers to extract thematic words and construct a semantic affiliation organization.

III. PROPOSED SEMANTIC ASSOCIATION FRAMEWORK BUILT ON ONLINE REVIEWS

The proposed methodology has been conferred in this section.

A. RESEARCH DESIGN

To categorize riders' prospective requests from online travel reviews and develop rider pleasure, offered a semantic association analysis method for applied strategy plans in fields associated with opinion mining, as shown in Fig 4.

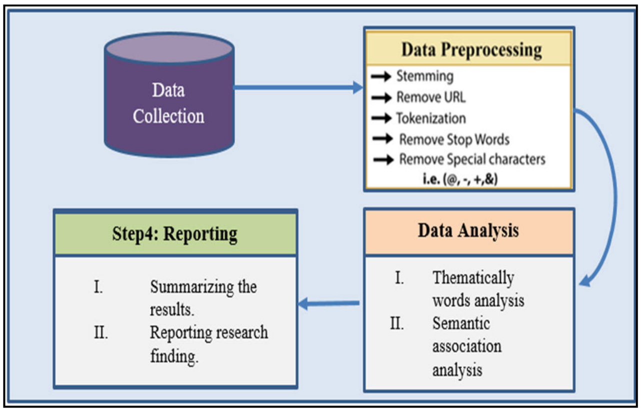

FIGURE 4. Semantic Association Framework built on online reviews.

B. DATA COLLECTION

In the preceding work, most research articles used the single raised area to gather data on online travel reviews [55]. To attain the most illustrative facts in this research study, we select two major platforms (Uber, and Careem) as the source of the truth and extract online travel reviews using Python programming language. Careem and Uber are the highest two Pakistani companies and central new business to customers traveling e-commerce websites and applications. We collected review data on the top two traveling companies in Pakistan (Uber and Careem). Whenever customers required a ride, they will get a ride in minutes. Or become a car driver and make money according to their agenda. Uber traveling company knows better ways to work, move and succeed in Pakistan. Careem is a vehicle (Mini, Go, Go+, and Bykea) for hire company that is a subordinate of Uber's American company. It is created in Dubai, with actions running in more than 100 cities, spread over more than 15 states including the East, Africa, and South Asian countries.

C. DATA PREPROCESSING

The whole reviews gathered from the two nomadic companies' platforms (Uber and Careem) were pre-processed by three actions: data cleaning, tokenization, ending word, and repeated word removal. Cleaning of data used to notice and erase incorrect/unusable reviews from the reviews dataset, like mistakes in spelling and non-target language [4] separating only important rider-related data and facts. According to this research work, we first removed the sent reviews from riders with a literal size of a minimum of 10 words. Review size affects perception if the textual size of reviews is minimum then it affects perceptions [21]. Moreover, originating information value was pitiable when the size of reviews is less than 10 words [57]. Additionally, since numerous recurrent statistical biases on reviews were sent by riders, if the rider sent the same review twice then we keep only one record from the rider's repeated reviews.

TABLE 2. Results after cleaning data.

Sr#	Review Platform	No of Reviews
1	Uber	2384
2	Careem	1380

As a decisive point, we removed the reviews that were commercials to confirm the truthfulness and accuracy of the data testers. Table 2 offerings results after data cleaning. We take two datasets of Uber and Careem from Kaggle with 2,384 reviews from Uber, and 1,380 reviews from Careem.

IV. RESULTS

The analysis of outcomes has been discussed in this section.

A. STATISTICAL ANALYSI OF THEMATIC WORDS

To find the correct essence of the context, a simple frequency analysis of thematic words is usually not recommended. For example, [24] reasoned that guesthouse subjects include thematic words such as bedroom (e.g., room facilities, sight, relaxed), locality (e.g., environment, near the airport), and conveyance (e.g., vehicle, car parking). According to [56], the physical charm, sense of comicalness, and superiority of trip guides were significant features affecting their interfaces with travelers, and the context should be deliberated in the cataloging of thematic words.

The procedure of manual content analysis in this research article was as defined. First, we combined the thematic words of two platforms and designated the top 50. The designated thematic words were characterized by three specialists in e-commerce conferring to the condition that thematic words with comparable attributions were gathered into classifications by analyzing their interrelation and rational order. As an outcome, we recognized four topics: ride guide, facility, scenic spot, and understanding. Moreover, defined all topics to decrease the considerate bias in the next arrangement [55].

In [26] represents some bigram co-occurrence phrases of each online traveling agency. Assign the weight to each bigram phrase that represents the occurrence of thematic words. Table 3 shows the top four bigram co-occurrence phrases of every online traveling organization. Table 2 represents the detail of the reviews, from datasets of reviews of Uber and Careem. We select the bigram co-occurrence phrases and assign weight. The weight represents the collected value of the co-occurrence of two thematic words.

TABLE 3. Bigram co-occurrence phrases on the two platforms.

UBER		CAREEM	
Bigram phrase	Weight	Bigram phrase	Weight
horrible accident	**15**	horrible accident	**18**
ride–explanation	**1005**	ride–explanation	**870**
ride–satisfaction	**575**	ride–satisfaction	**540**
Guide-happy	**560**	Guide-happy	**660**

As shown in Table 3, the top 4 bigram co-occurrence phrases on Uber and Careem are very similar, as horrible-accident ride–explanation, ride–satisfaction, are most frequently mentioned by users, meaning that the travel itinerary and the service quality of the traveling were extremely important factors for the users of Uber and Careem.

The overall facility excellence of ride guides or captain is responsible for the satisfaction of riders and influence riders' decisions in the selection of all-inclusive rides [58]. Fig. shows the relative differences of four bigram co-occurrence phrases on Careem company. The X-axis represents the bigram phrases which are shown in table 2. The Y-axis represents the weight of that bigram phrase. The "ride-explanation" bigram phrase has the highest weight 870 and the "horrible-accident" bigram phrase has the lowest weight 18. However, ride-satisfaction has 540, and guide happy has 660 weights, respectively.

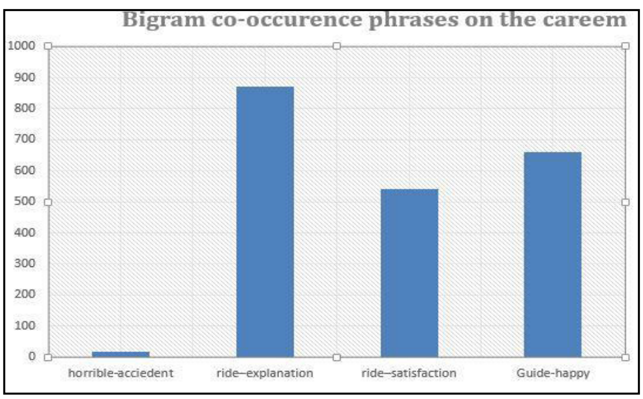

FIGURE 5. Bigram co-occurrence phrases on the Careem.

Fig 6 shows the relative differences of four bigram co-occurrence phrases on Uber traveling company. The X-axis represents the bigram phrases which are shown in table 2. The Y-axis represents the weight of that bigram phrase. The "ride-explanation" bigram phrase has highest weight 1005 and the "horrible-accident" bigram phrase has lowest weight 15. However, ride-satisfaction has 575 and guide happy has 560 weights, respectively.

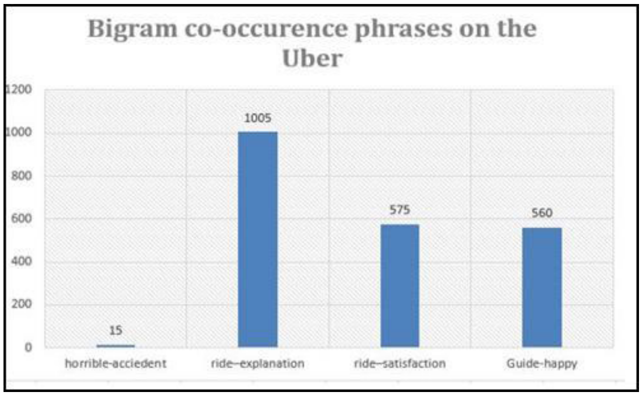

FIGURE 6. Bigram co-occurrence phrases on the Uber.

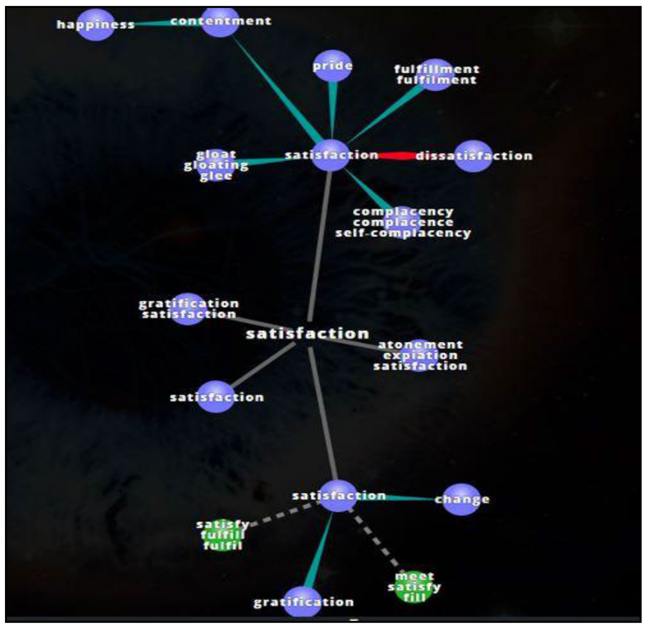

FIGURE 7. Network Visualization of thematic words.

Visualization is the revolution of textual data into a graphical representation of a network using thematic words that represents the edges among thematic words in the form of nodes and lines [26]. To create the semantic association of thematic words more instinctive, Gephi is used for the network visualization in this research article. We use the layout of VisuWord to draw a network graph. Associate with other layout algorithms, ForceAltas2 has a better-measured quality [59], [60]. The stable state graphs of Uber and Careem are shown in Fig. 7 and Fig. 8, respectively.

From millions of reviews, got from two significant web-based travel organizations in Pakistan, a semantic affiliation

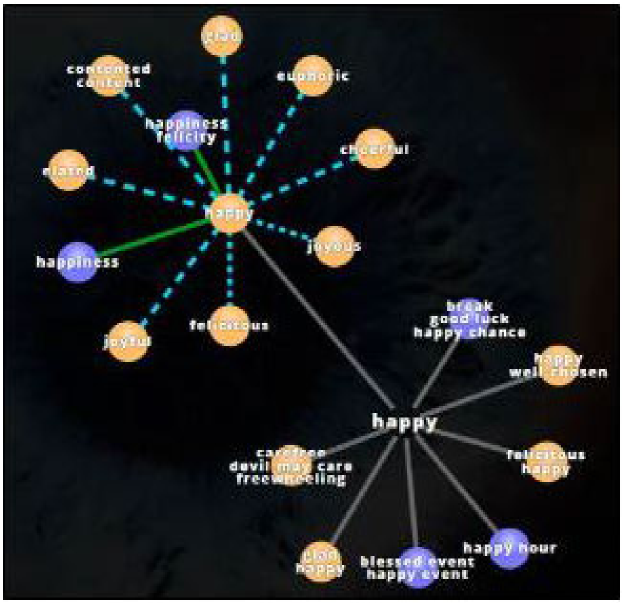

FIGURE 8. Thematic word visualization.

examination was utilized to extricate topical words and construct a semantic affiliation organization. The data reveals that there are evident differences in thematic words, subject distribution, structural features, and community links on different platforms. Fig. 8 represents some top thematic words selected from Uber online reviews datasets. Some riders sent the review they are satisfied with the facilities that Uber company providing to their riders.

Although some riders sent the review, they are not satisfied with the services that Uber company providing to their riders. Some of their riders sent them suggestions on how to improve their work.

V. DISCUSSION AND CONCLUSION

The analysis of outcomes has been discussed in this section.

A. MAJOR FINDINGS

This research work provides an irreplaceable research angle on online travel reviews. Online tourism evaluations are a valuable source of data for the tourism organization and defining whether they can be excellently recognized is critical to influencing tourism opinion-making using decision opinion. The main determination of this article is to recognize normal topics and connect them to contrasts in web-based travel reviews and feedback. From millions of reviews, got from two significant web-based travel organizations in Pakistan, a semantic affiliation examination was utilized to extricate topical words and construct a semantic affiliation organization. We move past the restrictions of earlier knowledge and familiarize social network theory in our research. Our research work can accurately categorize the main topics of online travel reviews and the social network associations formed by main topics. Our study originates that the Uber and Careem traveling companies are composed of two groups: guides and rides. There are some other sub-groups in the travel and ride group, such as the sub-group of happiness, the sub-group of explanation, and the sub-group of travel guidance. There is a strong linkage between the explanation subgroup and the guide group. This explains the phenomenon that consumers usually consider the information provided by the guide provided at a similar time. This research also concludes that it is necessary to enhance the explanation capability of rider guides as these guides are the most critical and easily accessible source of information and this facilitation will help in increasing the satisfaction of riders on Uber and Careem.

B. IMPLICATION FOR RESEARCH

First, this research work offers a distinctive research perspective on online travel reviews. We transfer past the boundaries of previous studies and familiarize social network theory in our research work. This research work grips that online travel reviews reflect the social interface between reviewers and travelers, which signifies a type of social association. This research work grips that online travel reviews are a mirror of the social collaboration between reviewers and riders, which shows a type of social association. Social networks, which are agreed as social relationships, mention all formal and informal social associations within a group of exact people, together with the indirect social associations connected by the somatic environment, national sharing, and direct social association (Mitchell, 2010). Hence, these thematic words identified through online travel reviews are kinds of a node that helps in identifying the connections or semantic associations among them. These nodes and semantic connections together represent the social networks of online travelers. This provides new avenues for research and in-depth analysis in the field of online traveling and on larger scales, its scope includes the application of social network theory. The analytical framework used in the study provides novelty and for extraction of main areas of concern, issues, and problems from the databases of online travel reviews to help people find solutions to their problems. The finding of the study is a hypothetical development contribution in the field of online travel reviews research with the help of semantic association analysis.

This study also reveals the network relationship through visualization accurately. Thematic extraction of the words was used to construct the bigram co-occurrence phrases with the help of semantic association. VisuWord was used to create a network graph of these associations. This graph is used to explain the complex relationships between the core topics keeping the word granularity perspective. This helped in overcoming the shortcomings of the previous studies in terms of accuracy effectively [24].

C. LIMITATIONS AND CHALLENGES

Good research always acknowledges the limitations involved in the study. The current study is limited by some notable.

First is the size of the sample which is taken from basically two sources which are Careem and Uber. Other such platforms like Bykea or Indrive could also be included because of time constraints and budget constraints such large-scale data collection was not feasible for the principal investigator. Future research can include these to get a better understanding of the topic. The second, limitation is the data processing techniques used in the study. In the present study, data cleaning, tokenization, and repeated word removal were used. These techniques such as thematic analysis can also be employed to get a better understanding of the data and interpretation of the data effectively.

D. CONCLUSION AND FUTURE WORK

Current study was performed under some limitations and directs future research in the field of semantic association analysis. First, the results of this study are based on a dataset of two major online traveling companies (Uber, and Careem) in Pakistan. Below the situations of the quick incorporation of e-commerce into travel, online travel-raised areas have appeared all over the world. The outcomes of this research work might not be generalizable to other attractive spots and international travel companies. Future research can expand the nature of the research and can include different international factors or the factors of destination or cultural difference to enhance the generalizability of the research. Secondly, in the current study, the time period for the selection of travel reviews was after 2015, hence, future research may expand the research time frame to better assess the outcomes of the research and to find more facts to authenticate the conclusion of the study. Thirdly, this research only considered the structural belongingness of the semantic association of networks through studying online travel reviews. These included average clustering coefficients, modularity, and density. The missing elements were the performance of the tourism products and their structure properties, which can be considered in future research to make research more authentic and generalizable.

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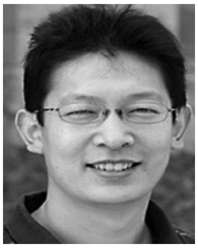

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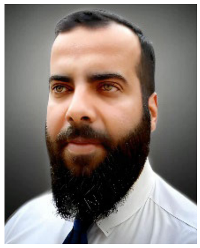

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