# Insight from User Generated Review of Oil and Gas App: A Topic Model Approach


## Abstract

India, as one of the world's fastest-growing economies, has a significant and rapidly expanding energy demand. The country heavily relies on oil and gas resources to meet its energy requirements for various sectors, including transportation, power generation, and industrial production. The Indian Oil and Gas industry is growing rapidly and playing an important role in the development of the Indian economy. Being a major consumer of energy resources, India has limited supplies of oil. The demand-supply gap however is very high. The structured industry note gives an overview and insights into the Indian Oil & Gas industry as a whole. It also appraises the emerging current scenario of the Indian Oil & Gas industry. It further measures the progressive step taken by the government towards India's energy security through the creation of conductive policy and regulatory framework to promote Exploration & Production, Refining, and Retailing of Oil and Gas for competitive and healthy growth of the industry and country as a whole.

This study explored the Google Play reviews of HPCL, BPCL, and IOCL (an aggregated e-government mobile application of the Government of India). We aggregated 126600 reviews provided from 17-11-2018 to 17-05-2023. Subsequently, we extracted ten topics related to customer experiences by using latent Dirichlet allocation, an unsupervised machine learning algorithm. The following topics were identified—OTP-related experience, User experience, Delivery Experience, Product feature and communication experience, App Functionalities, Linguistic limitations, Payment and booking experience, User Compatibility Experience, Perceived Usefulness, and Customer satisfaction. Finally, we calculated the relative importance of the identified topics and topic-wise sentiment polarity.



## Keywords

Oil and Gas industry, User generated review data, latent Dirichlet allocation, machine learning


## Introduction

Competition in the oil and gas industry is characterized by a complex and dynamic landscape shaped by various factors, including global market dynamics, geopolitical influences, technological advancements, and environmental concerns. Several key players vie for market share and strive to position themselves as leaders in this highly competitive sector. The oil and gas industry in India is marked by robust competition among various companies operating in the sector. India, being one of the world's fastest-growing energy consumers, has a significant demand for petroleum products, making it an attractive market for both domestic and international players. Competition in India's oil and gas industry is driven by factors such as pricing strategies, product quality, distribution network, customer service, and technological advancements. Hence companies continuously strive to enhance their market presence, improve operational efficiencies, and meet the evolving energy needs of the Indian population. In today's digital age, user-generated content has become an invaluable source of information and feedback for businesses across various industries.

Hence the gas and oil sector is no exception, as companies like Hindustan Petroleum Corporation Limited (HPCL), Bharat Petroleum Corporation Limited (BPCL), and Indian Oil Corporation Limited (IOCL) recognize the significance of user reviews in shaping their products and services. User-generated reviews provide an authentic and real-time glimpse into the experiences and opinions of customers who have interacted with these companies' mobile applications.

These applications have become integral tools for users to manage their fuel needs efficiently, discover nearby fuel stations, make payments, and access exclusive offers and rewards. This article explores the vast potential of user-generated reviews as a valuable source of data, focusing specifically on the experiences shared by users of HPCL, BPCL, and IOCL apps. By analyzing these reviews, we can gain insights into customers' satisfaction levels, identify areas of improvement, and understand emerging trends in the gas and oil industry. The reviews encompass a wide range of topics, including app performance, user interface, functionality, customer service, and overall user experience. By tapping into this trove of user feedback, HPCL, BPCL, and IOCL can enhance their app features, address pain points, and develop customer-centric solutions that align with the evolving needs and preferences of their users. Additionally, studying user-generated reviews helps foster transparency and accountability between companies and their customers. It allows these organizations to actively listen to their users, engage in two-way communication, and demonstrate their commitment to providing exceptional services. This article delves into the key insights extracted from the user-generated reviews of HPCL, BPCL, and IOCL apps. It aims to shed light on the strengths and weaknesses of these applications, highlight customer satisfaction drivers, and offer recommendations for future enhancements. As user-generated content continues to shape the landscape of consumer decision-making, it is crucial for gas and oil companies to leverage this data effectively. By prioritizing user feedback and integrating it into their decision-making processes, HPCL, BPCL, and IOCL can deliver more seamless and user-friendly experiences, reinforcing their position as industry leaders. Join us as we embark on a journey to unlock the power of user-generated reviews and understand how HPCL, BPCL, and IOCL can harness this valuable resource to drive innovation and elevate customer satisfaction in the gas and oil industry. Most studies have performed a sentiment analysis to extract insights from UGC (Alaparthi & Mishra, 2021; Ibrahim et al., 2017) and not used more advanced machine learning algorithms, such as latent Dirichlet allocation (LDA) (Mishra, 2021; Reisenbichler & Reutterer, 2019). Although machine learning techniques are widely used in the industry, the marketing literature does not utilize their potential adequately (Wedel & Kannan, 2016). Only ten studies in core marketing journals have used topic modelling from 2008 to 2017 (Reisenbichler & Reutterer, 2019).

## Theoretical Foundation

According to stimuli-organism-response (S-O-R) theory, emotional feedback (such as pleasure, arousal, and other subjective feelings) mediates the relationship between envi- ronmental stimuli and behavioural responses (Mehrabian & Russell, 1974). These emotional feedbacks are relatively automatic and are based on past, personal, or observed expe-rience (Shah, 2020). The S-O-R model has been used to explain the role of experience in stimulating customers' inner feelings and post-consumption behaviour (Chopdar & Balakrishnan, 2020; Xue et al., 2020). Studies from con- sumer behaviour, psychology, and sociology suggest that the effect of consumer experience is a powerful motivator for different types of post-consumption behaviour, including theelectronic word of mouth and repurchase intention (Sundaram & Hills, 1998; Westbrook, 1987). Different con- sumption experiences produce different subjective feelings and thus different motivations to write the review (Sundaram & Hills, 1998). When a citizen experiences an e-government service they will have different emotional feedbacks depend- ing on service experience and their past, personal or observedexperience. These emotional feedbacks create differentmotivations to write reviews which eventually leads to shar-ing user experience in the review.

Other theories which are used to connect the user experi-ence and online reviews are equity balance theory (Belarmino & Koh, 2018) and agency theory (Mishra, 2021). Equity bal- ance theory posits that when individuals face discrepancy between inputs and outputs they will adjust the inputs to seek equity (Adams, 1963). Therefore, whenever users receive positive and negative experiences, they want to bal-ance the relationship with the service provider, motivating them to write online reviews (Hennig-Thurau et al., 2004). Equity theory, however, cannot explain many external andsocial motivations to post the reviews. For example, the benevolent people want their inputs to be higher than the outputs they receive and therefore have altruistic motivationto write the review (Huseman et al., 1987). Another type of individuals who seek imbalanced relationship are people who want their output more than their inputs and, therefore, write reviews with self-enhancement motivation, that is, with the desire to be seen as experts (Hennig-Thurau et al.,2004; Huseman et al., 1987). According to agency theory, diverse goals of principles and agent, and principles' inabil- ity to ascertain appropriateness of agent behaviour results in agency problem (Eisenhardt, 1989). Therefore, self-interest behaviour service provider (agent) creates agency problemand drive user (principle) to engage in social sharing of theexperience (Mishra, 2021). Agency theory only explains themotivation to write review if the experience is negative.

Unlike agency theory and equity theory, S-O-R theory is more generic and can explain user motivation to write reviews in case of extremely positive and negative experiences as well as other social and external motivationwhere individuals seek deliberate equity imbalance.Overall, the S-O-R framework can effectively capture psychological process of writing customer review. Using the S-O-R framework this study aims to link citizen experience of e-government services (S) with motivation to review (O) and citizen review (R). Figure 1 presents the research framework for this study with the examples of reviews written with different motivations.

Several studies have considered user experience as a crucial stimulus affecting consumer behaviour in e-services (Constantinides, 2004; Pantano & Priporas, 2016). Various customer experience categories have been used as stimuli inthe e-service literature—aesthetic appeal, layout and functionality, financial security (Tankovic & Benazic, 2018)
, task cues, aesthetic cues, and social cues (Tang & Zhang, 2020). The above discussion on the S-O-R frameworksignifies the appropriateness of citizen reviews to gain insights into citizens' experience of e-government services.

## Methods

This study used the method proposed by Geetha et al. (2017)to determine whether reviews represent citizens' experience. We replicated the framework used by Mishra (2021) and Tirunillai and Tellis (2014) for extracting customer

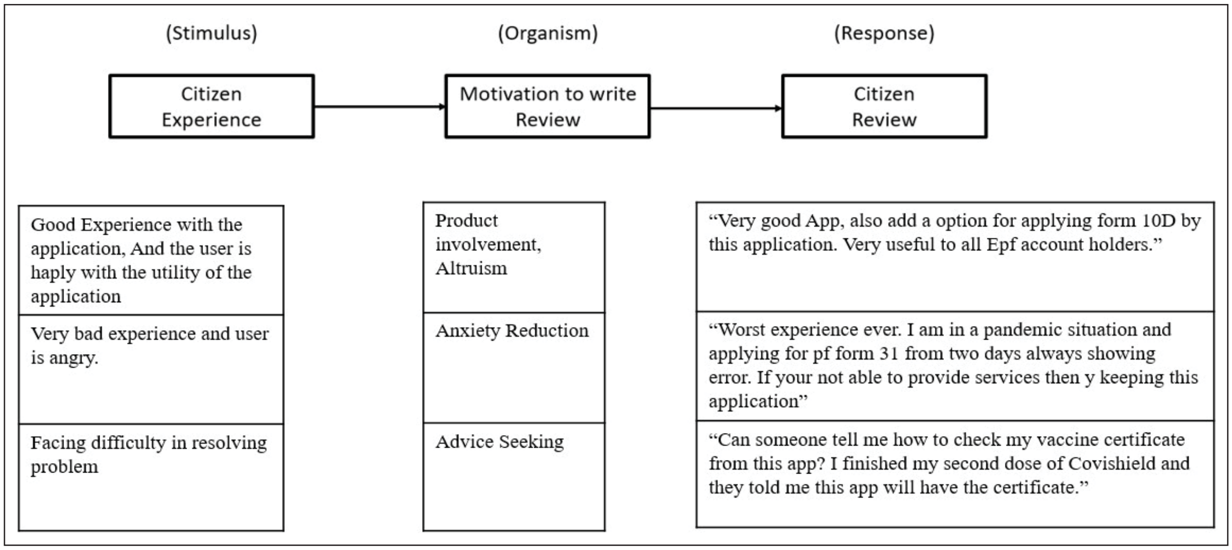


**Figure 1.** Research Framework.

**Source:** The authors.

experience topics from citizens' reviews by using LDA, followed by the labelling and validation of extracted topics. Finally, the review was assigned to the most suitable topic to understand topic-wise sentiment and relative importance. The process followed in this article is illustrated in Figure 2.

### *Sample*

The Google Play reviews of the Oil and Gas application was extracted (BPCL, HPCL and IOCL mobile application). As the world's main fuel sources, oil and natural gas are significant players in the energy sector and have an impact on the global economy. Data from User-Generated Content (UGC) can provide insightful information on how the oil and gas sector operates on a daily basis. Users can discuss their opinions, experiences, or suggestions regarding particular procedures, tools, or services. The oil and gas business can benefit from market intelligence provided by UGC data, which can also provide real-time information on potential safety risks and environmental incidents. India currently has 750 million smartphone users, and this number is expected to reach 1 billion by 2026 (India to have 1 billion smartphone users by 2026: Deloitte, 2022). Thus, these mobile application (BPCL, HPCL and IOCL) are the ideal choice for this study. In this study, 126600 qualified users (52779 of BPCL, 13962 of HPCL and 59859 of IOCL) generated reviews were analyzed during the time period 17-11-2018 to 17-05-2023.

### *Validation of User Review*

Online ratings provided to the application are citizens' satisfaction scores with the application (Engler et al., 2015).

### *Pre-processing of Reviews*

Prior to statistical analysis, the data should be pre-processed. Text data in its raw form cannot be utilized (Mishra, 2021). We started by removing punctuation and digits from the data. Second, we changed the data into lower case for standardization. The NLTK corpus was then tokenized, and we eliminated all stop words. Fourth, all the words were lemmatized to reduce them to their basic forms so that terms like "go" and "going" were not taken into account individually. The list of words utilized for the ensuing analysis was created from the outcomes of the aforementioned steps.

Using the Genism 3.8.0 package, the collection of words was joined to yield two- and three-word phrases (bigrams and trigrams, respectively) (Rehurek & Sojka, 2010). To guarantee the selection of only bigrams and trigrams that appeared at least ten times, the threshold value was set at 10. The original bag of words was expanded to include all the bigrams and trigrams. To exclude outliers, further words with document frequency in the bottom 20% and top 20% were eliminated.

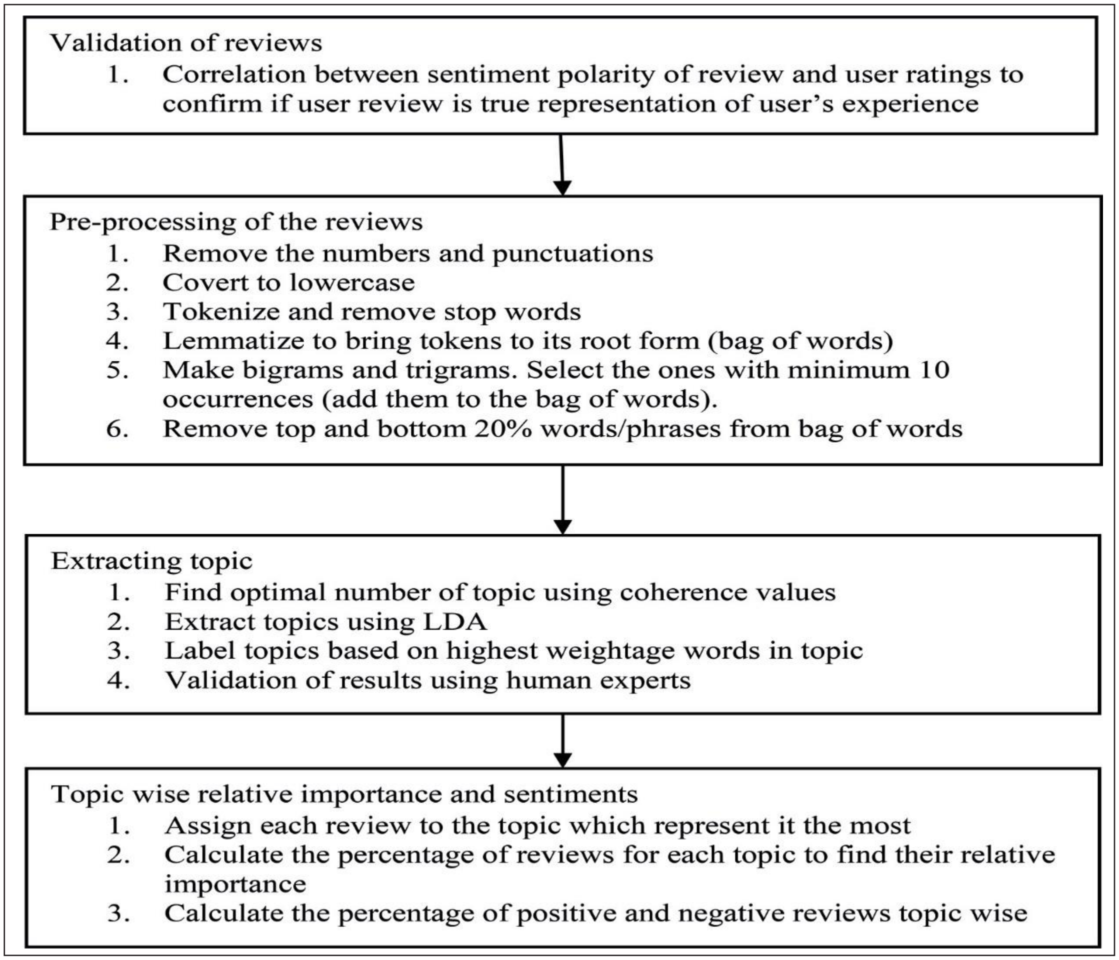


**Figure 2.** Process.

**Source:** The authors.

## *Extracting Topics*

For the analysis of reviews, there are some restrictions. The IOS application received several reviews, with an average of 22 reviews each day (Pagano & Maalej, 2013). Second, the reviews' quality varied; they may contain an insult, criticism, bug report, complaint, suggestion for a feature, or a compliment. Third, a review will contain a range of emotions, and the rating sums up the overall feeling, which is a mix of good and negative. LDA is an excellentmethod for handling such complexity. As a generative model, LDA accounts for the way topics in the documents influence the distribution of words within review in accordance with certain probabilistic sampling norms (Blei et al., 2003). Or we can say, each review document reflects different dimensions of customer experience.

LDA determines this distribution of latent dimensions, assuming that the number of topics (K) is fixed across all the review documents (D) combined. Each review document (D) is a multinomial probability distribution ($\theta_d$) of topics (K). Each topic (K) is a multinomial probability distribution ($\theta_k$) of words. Based on these assumptions, each word is assigned to the most suitable topic (Blei et al., 2003). With these presumptions, LDA can make inferences about the distribution of topics across documents ($\theta_d$), the distribution of words across topics ($\theta_k$), and the assignment of topics to individual words ($Z_{dn}$) in each of review documents (D). Multinomial distributions are used to model both topics ($\theta_k$) and documents ($\theta_d$), while Dirichlet distributions are used to model the hyper parameters α and β of topic distribution for each document ($\theta_d$) and word distribution for each topic ($\theta_k$), respectively. Estimates of the model's latent variables are obtained by taking a sample from the posterior conditional distribution using collapsed Gibbs sampling by applying the Markov chain Monte Carlo method.

LDA efficiently gathers context-specific data. Regarding the distribution of resources and the grammaticality of the language, the algorithm makes no assumptions. With little assistance from humans, LDA can provide realistic dimensions (Guo et al., 2017).

LDA is a strong method since it can provide themes even when used on material that has already been processed (Tirunillai & Tellis, 2014). Compared to other subject modelling algorithms, LDA is the most popular and efficient (Guo et al., 2017; Reisenbichler & Reutterer, 2019). LDA is hence appropriate for our study.

Although user experience can have many different aspects, people might not write about them on a public forum. Users frequently reserve their most noteworthy experiences for sharing (Tirunillai & Tellis, 2014). As a result, not all dimensions will be present in every review, but the overall corpus would include a range of experiences and viewpoints, creating a sparse document word matrix (Mishra, 2021). Customers convey many aspects of their experience in various ways (Mishra, 2021).

We initially identified the terms in the review corpus that have the strongest associations with the themes to be labelled. Then, each topic is given a label that encompasses all of the words contained in the topic (Tirunillai & Tellis, 2014). The procedure adheres to that employed in the research that has already been done on the topic of naming (Guo et al., 2017; Mishra, 2021; Tirunillai & Tellis, 2014). We duplicated the procedure outlined in earlier studies (Mishra, 2021; Tirunillai & Tellis, 2014) in order to validate it.

A collection of 100 reviews was chosen at random, along with the topic name and words connected to it, and two skilled human raters (one from the market research sector and one from academia) were given this information. According to the theme words, we asked them to summarise the subjects. In order to establish how closely the themes selected by the human raters and LDA align, the kappa coefficient between the two was determined (Fleiss, 1971).

### *Topic-wise Relative Importance and Sentiments*

Each review contains different topics in different proportions, and because users share only the salient dimensions of experience, the distribution is skewed towards a few topics (Mishra, 2021). We assigned each review to the topic with the highest weightage in that review. Then, we calculated the relative percentage of each topic. Additional reviews with polarity greater than zero, less than zero, and equal to zero were classified as positive, negative, and neutral reviews, respectively. Finally, the percentages of positive, negative, and neutral reviews were calculated.

## Results

We first examined the correlation of sentiment polarity and review ratings. Second, we explored the extracted topics, followed by their labelling and validation. Finally, we determined the relative importance of the extracted topics and topic-wise sentiments.

### *Validity of Reviews*

We looked at the association between the sentiment polarities of user ratings and reviews to validate our findings. With a correlation coefficient of 0.57, the findings showed a substantial link between sentiment polarity and review scores. According to this result, reviews serve as a representation of customer satisfaction levels, and they may be studied to learn more about how users felt.

### *Topic Extraction*

We used the Genism package to extract topics (Rehurek & Sojka, 2010). For each of these topics, coherence values (CVs) were calculated. CVs examine the tightness of a dataset's clustering structure (He et al., 2009). CVs were used to find the optimal number of topics. A higher CV suggests abetter model (Hasan et al., 2020). The optimal number of latent citizen experience topics was ten.

We identified ten words from the topic—word matrix of ten topic solutions with the highest weightage. Ten topic solutions obtained from LDA with the top ten wordsfor each topic are listed in Table 1. These words were thenused to label the topics and determine the characteristics ofthe topic's customer experience dimension. For example, topic one represents OTP-related experience

Ease of user experience is the second topic that describes the user experience of handling the application, its service, fast and smoothness. Can't check booking history, can't chat support, login error, UI interface. Suggestions were provided to add such features and improve the application. The third topic, labelled as Delivery and customer interface experience based on words associated are related to smooth and easy booking and delivery of gas cylinder i.e. delivery turnaround time, contains reviews that represent delays in service delivery or delight due to fast service. The fourth topic, labelled Product Feature and communication experience, contains reviews that represent the product features. The fifth topic is related to the functionalities of the application and technical issues encountered by citizens while using the application, such as errors, service not available, and server crash. The sixth topic is labelled as Linguistic Limitation, this represents problems that user face while selecting mode of language in the app.

**Table 1.** Topic wise terms.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **OTP-RELATED EXPERIENCE** | Excellent | App | Worst | OTP | Change | Number | Superb | Mobile | Slow | Address |
| **EASE OF USER APPLICATION OR USER EXPERIENCE** | Service | Good | Ok | Fast | Apps | Indian | Oil | Work | Thanks | Thank |
| **DELIVERY AND CUSTOMER INTERFACE EXPERIENCE** | Easy | Gas | Cylinder | Use | Delivery | Booking | Bad | Book | App | Customer |
| **PRODUCT FEATURE AND COMMUNICATION EXPERIENCE** | Good | App | Application | Comfortable | Goog | Sarvis | Effective | Product | Idea | Communication |
| **APP FUNCTIONALITIES** | App | Login | Time | HP | Error | Password | Unable | Awesome | Able | Connection |
| **LINGUISTIC LIMITATION** | Nice | App | Experience | Application | Language | Tamil | Smooth | Class | Work | wow |
| **PAYMENT AND BOOKING EXPERIENCE** | Payment | Online | App | Working | Option | Pay | Money | Booking | Time | UPI |
| **USER COMPATIBILITY EXPERIENCE** | Super | User | App | Friendly | Helpful | Poor | Point | Interface | Response | Reward |
| **PERCEIVED USEFULNESS AND FUNCTIONALITY** | App | Update | Option | Time | Issue | Need | Booking | New | Problem | Like |
| **CUSTOMER SATISFACTION AND FUNCTIONALITY** | Best | App | Useful | Great | Hai | Aap | Nahi | hi | ho | se |

**Source:** The authors.
**Note:** *UPI (unified payment interface) is an Indian system that powers multiple bank accounts in one application and is unable to seamless fund routing.

The seventh topic is based on experience with payment and booking of the oil and gas because oil and gas app has many services that require payment to be made. Similarly, topic eight defines the user compatibility experience i.e. how compatible the users are with the interface of these mobile application whereas topic nine deals with the functionalities and technical issues of these mobile application. Topic ten defines the overall satisfaction of customer with the application. Topic definition along with a verbatim review example is listed in Table 2.

The validation of the extracted topics was carried out by determining the inter-rater agreement between two human raters and automated output generated using unsupervised LDA. The Fless'kappa (k) coefficients for randomly selected reviews related to the ten topics between—(a) LDA topics and human rater one; (b) LDA topics and human rater two;and (c) human rater one and human rater two were 0.53, 0.71, and 0.62, respectively. Since The Fleiss' kappa inter-rater agreement for 100 randomly selected reviews over ten possible topics among the automated rating and two human raters was found to be 0.62 and the kappa coefficient of 0.65 is considered to indicate a moderate or substantial agreement (Landis & Koch, 1977). Given the subjectivity of the task, the *k* values of 0.53 and 0.62 can be regarded as significant (Tirunillai & Tellis, 2014). They further opine that given the subjectivity inherent in the task, this value indicates a "moderate to substantial agreement between the two raters and the automated analysis". Therefore, we concluded the validity of the automated topic assignment by LDA.

**Table 2.** Topic definition and verbatim.

| Topic | Definition | Verbatim |
|---|---|---|
| *OTP related experience* | *Contains reviews related to userexperience with regard to OTP* | *The worst experience with this app. OTP not received until 30 mins.*<br>*Worst app ever, irritating, late otp, totally disappointing* |
| *User experie nce* | *Contains reviews related to user experience in handling the application* | *nice simple application. good. keep. update makes simple. thank valuable support.*<br>*cheap service even n't care customer service completing last 1 year n't replay call poor & 3rd class service .* |
| *Delivery experience* | *Contains reviews related to delivery features and customer interface* | *app pretty easy user-friendly. discourage social evil paying extra delivery person.*<br>*good app. can't look feedback. refill delivered mode payment known. wanted pay online delivery, cannot allow. even delivery people can't know whether booked.* |
| *Product feature and communicatio n experience* | *Contains reviews related to the communication experience of the users and product functionality* | *good app transport business.*<br>*app good can be conveniently handled.*<br>*good app ... used refill app response good.* |
| *App Functionalities* | *Contains reviews related to functionalities of the app.* | *bad experience, login, giving error, unable send otp. bad ui, customer handling. can't support option well.*<br>*get error saying unable send sms. registered phone number gas connection different phone installed app registered phone feature phone cannot install app phone. number use receives otps and nothing else. u force customer use phone number.* |
| *Linguistic limitations* | *Contains reviews related to language interface* | *app logging language aware. option change language setting. whereas screenshots provided description show choose language.*<br>*please maintain language dashboard properly kannada language dashboard Telugu instruction joke* |
| *Payment and booking experience* | *Contains reviews related to user payment experience for availing various services like bill payment* | *multiple time happens money got deducted account, LPG can't book. one payment mode, issue debit card, credit card, upi, wallet. can't fix issue, requesting please can't add payment option 's working.*<br>*everything good, make payment online won't reflect app. lost money twice contacted customer care service said money refunded can't happen. started using cod option booking.* |
| *User Compatibility Experience* | *Contains reviews related to experience with the customer careand support in resolving issues* | *need improvement user friendly interface faster quick responsive.*<br>*good app booking LPG tracking. quick response user friendly experience. nice ...* |
| *Perceived Usefulness* | *Contains reviews related to product utility and function it performs* | *functionality working. 1. `` refill history " show delivered one. option track pending/current transaction, right?? 2. notification message app track recent booking. even notification indicate payment successful 3. 60 % online transaction failing billdesk option retry payment. old basic. developer dumb!!!* |
| *Customer satisfaction* | *Contains reviews related to the performance of app* | *great improvement pervious vision app. handling easy*<br>*surprised app good . clean ui ! ! everything flawless . mera desh badal raha .*<br>*experience company app always best. best every way. speed courtesy rank best.* |

**Source:** The authors.

**Table 3.** Topic-wise sentiment and relative importance.

| Topics | Negative | Neutral | Positive |
|---|---|---|---|
| OTP-related experience | 8% | 44% | 48% |
| User experience | 4% | 12% | 84% |
| Product feature experience | 1% | 1% | 98% |
| App Functionalities | 46% | 20% | 34% |
| Linguistic limitation | 1 % | 7% | 92% |
| Payment and booking experience | 39% | 26% | 35% |
| User compatibility experience | 10% | 19% | 81% |
| Perceived usefulness and functionality | 29% | 29% | 42% |
| Customer satisfaction and functionality | 5% | 25% | 70% |
| Delivery experience | 25% | 18% | 57% |

**Source:** The authors.

### *Topic-wise Analysis*

To examine the relative importance of the topic and topic-wise user sentiments, we first assigned each review to the topic that most effectively represented it. User reviews contains topics in different proportions; however, the assumption is that reviews are skewed towards a topic (Tirunillai & Tellis, 2014). The assumption can be made because users generally write regarding their experience'smost salient dimension (Mishra, 2021). We calculated the relative importance by assigning 100% to the topic with the highest reviews and the relative percentage to theremaining topics.

Reviews with sentiment polarity greater than zero, less than zero, and equal to zero were tagged as positive, negative, and neutral, respectively. We calculated the topic-wise percentages of positive, negative, and neutral reviews. The analysis is presented in Table 3.

## Discussion

This study is the first to validate the use of citizen's reviewof the oil and gas applications (BPCL, HPCL IOCL) to generate insights into customer experience. By using the LDA algorithm, we determined ten topics for citizen's experience of these apps: OTP- related experience, Ease of User Application or User Experience, Delivery and customer interface experience, Product Feature and communication experience, App Functionalities, Linguistic limitation, Payment and booking experience, User compatibility experience, Perceived usefulness and functionality, Customer satisfaction and functionality. Finally, topic-wise sentiment and relative importance were examined. In this section, we discuss the theoretical origins of these topics.

Customer experience includes utilitarian characteristics (Gentile et al., 2007; Schmitt, 1999). The achievement of the user's aims is what determines a product or service's utilitarian value, which is less concerned with experiential value. Consumers that appreciate convenience and time savings are utilitarians. According to Zeithaml (1988), it alludes to the cognitive component of the attitude towards a good or service. The availability of utility features (perceived usefulness) and the experience with utility features (product feature experience) can both be used to assess the utility of a service. Therefore, the crucial aspects of citizen experience are perceived usefulness and product characteristics. Therefore, perceived ease of use is vital to gauge users' decision to use any information system (Davis, 1989). Perceived control over a mobile application depends on the ease and efficiency of accessing relevant information Therefore, ease of use is an essential experience dimension. Moreover, previous studies have linked perceived usefulness, ease of use, and product feature experience with customer experience.

The difference between the time the user expects the service to be delivered and the time the service is actually delivered is known as a service delay. The evaluation of service quality is significantly impacted by service delays (Taylor, 1994). The evaluation of service punctuality, a crucial element of service reliability, is impacted by delay (Parasuraman et al., 1985). The first time a user interacts with a mobile application is during login, making it a crucial experience dimension.

Technical issues with services are inevitable (Zhu et al., 2003). Customer discontent results from a poor evaluation of the service experience caused by a service failure (Chuang et al., 2012). Technology experience is a critical experience dimension since it is a key cause of service failure.
Service failures are unavoidable owing to both human and technology mistakes. Customers frequently start their service recovery process by contacting customer service for assistance. The company now has the chance to win back the trust and loyalty of its customers. According to Joseph & Stone (2003), the ability of an organisation to offer feedback and a fix for a service failure falls under the definition of customer care

service. It is similar to the responsiveness dimension of service quality (Yoon, 2010). Various studies have linked responsiveness with customer satisfaction and service quality). Therefore, customer care experience results in social sharing and thus UGC generation. Many Oil and Gas services require online payments. Users will be reluctant to share their financial information if they do not trust the service (Pandey & Chawla, 2018). Virtual payments at mobile applications are temporally separated; thus, trust has become a critical psychological factor affecting customer experience (Klaus, 2013). Therefore, a good payment experience increases confidence and satisfaction, and a poor payment experience leads to distrust and dissatisfaction

.

## Limitations and Directions for Future Research

While constraining LDA model to sentence level assumes that words within the sentence belong to same topic. Though in this study we have taken bigrams and trigrams, future research should consider sentence constrained model.

Future study in this field should be prompted by the limitations described in this section. The insights from UGC should be regularly tapped by leaders to manage citizen experiences in a proactive manner. Future research should examine various UGC sources and employ more sophisticated machine learning approaches to comprehend how citizens interact with the online mobile application for the oil and gas

There are several restrictions on the study that need to be addressed. The first drawback is the reliance on just one UGC source (reviews on Google Play). Reviews on Google Play are typically written by people who have tried the programme at least once. The citizen experience, however, can happen at any touchpoint, even if the programme isn't being used. The second factor that may influence a citizen's experience is a pre-existing attitude towards a service provider. Political convictions of the populace may also have an impact on the experience. However, this approach does not allow for the exploration of these dimensions. Third, it employs thebag-of-words approach rather than sentence-based LDA, which according to some researchers give better results (Büschken & Allenby, 2016). The bag-of-words model takes for granted that a document’s words contain information about its latent topics that can be reliablytraded.

## Conclusion

By distinguishing the elements of the citizen experience, their relative importance, and the level of citizen satisfaction with those qualities, this study made a contribution in this area. Experience is a dynamic, multidimensional concept that is challenging to quantify. By leveraging citizen reviews to extract readily available citizen experience, this study made the work easier. The difficulty of manually analyzing a large volume of review data increases the necessity for advanced machine learning approaches. Latent Dirichlet allocation, an unsupervised machine learning approach, was successfully applied in this work to glean insights on citizen experiences. Because of this, it is essential to consider all three of the research issues addressed by this study when building citizen-centric mobile applications for the oil and gas industry.