Analyzing Tourism Mobile Applications Perceived Quality using Sentiment Analysis and Topic Modeling

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***Abstract*—Mobile application is one of the most important information platforms for international tourists. Millions of tourists use mobile applications to find information and make transactions. Two popular Online Travel Agent (OTA) mobile applications for travel-related activities providers are Traveloka and Tiket.com. These applications certainly must meet travelers' needs to achieve satisfaction. Such satisfaction related to application Mobile Application Service Quality (MappSql) dimensions can be traced from thousands of their comments on the Google Play Store. From a set of reviews, information about the perception of mobile application quality can be obtained. Knowledge on user perceptions is very useful for company's consideration in creating effective business and app features to increase users' satisfaction. We propose Text Mining models to bring up hidden information regarding users' verdict. The selected text analysis methods for this research are Sentiment Analysis and Topic Modeling. We find that positive or negative sentiments towards MappSql dimensions of online travel agent applications qualities can be revealed using sentiment analysis method. Topic Modeling method is used to bring up groups of important words of topics related to each mobile application service quality dimensions.**

Keywords—Mobile Application Quality, Text Mining, User Satisfaction.

I. INTRODUCTION

Indonesia has a positive growth of internet users and tourism trends every year. Online Travel Agent (OTA) is one of the growing businesses in tourism industry. Over the past few years, tourism and hospitality industry companies have been taking part and developing their competitiveness in the applications market for e-commerce and online transactions activities [1]. OTA is a manifestation of the tourism business development using e-commerce technologies. In accessing OTA services, people prefer to use a mobile application compared to other platforms [2] which makes it very crucial for companies to improve as part of their service development.

Along with the development of technology, mobile application becomes an important role in accessing information. This is also true in term of users' reviews. Based on a study, online users' reviews have a significant influence on consumer product sales [3], so companies need to pay attention in gaining valuable insights. Google Play Store holds very large number of customers' reviews data. The number is growing fast. There are challenges to filter out low-quality reviews which may include unreasonable information, uncorrelated information to the product or a service, spam messages, or redundant information. With hundreds or thousands of new reviews every day, application developers and analysts will find it harder to filter and process useful information from these reviews [4].

Reviews within the mobile application marketplace usually reflect the user's positive and negative emotions [5]. For example, bug reports may contain negative sentiments, while user experience reviews may be combined with positive sentiments [6]. Sentiment Analysis as a method in Text Mining technique can be used to classify unlabeled data based on learning classification machine learning model concept using labelled training data. A trained sentiment analysis model will predict large number of unlabeled reviews in terms of positive and negative polarities automatically and quickly. This method can be applied in exploring application users' emotions so that developers can find out whether their applications invite more positive or negative sentiments.

We also select Topic Modelling method to reveal outline of users' reviews topics. We had focused our research on two of the most popular OTA providers in Indonesia which were Traveloka and Tiket.com as reported by DailySocial.id (2018). Traveloka and Tiket.com present the trending OTA e-commerce services. Results from both methods will serve as the basis of quality perceived comparison analysis purposes.

We consider topics discovery towards MappSql since it provides a scale and dimensions to assess mobile application service quality. MappSql is tailored for use in measuring mobile application service quality and is inferred from e-Service quality dimensions used in state-of-the-art researches. To the best of our knowledge, our research is the first work that incorporates sentiment analysis and topics modelling towards MappSql for a more comprehensive and unified measurement purpose.

Using appropriate data analytics tools, one can explore customer feedbacks in almost real-time manner. This will benefit OTA mobile applications developers in better tuning features of their respective products and services. In business management context, quality of general decision making will be improved correspondingly. Any data analytics method requires a reliable source of data. Since Google Play Store stores huge amount of users' bug reports, feature requests, and praises, it has becoming an important data source for mobile application engineering decisions [4].

II. LITERATURE REVIEW

Social media allows customers to share opinions and provide feedback about their usage experiences of many products and online services. Due to advances in database management techniques, social media channels business models, and mobile devices technologies, a lot of customer-related information is increasingly accumulating in social media companies. The use of social media channels technologies and big data analytics tools complement each other because the variety of social media channels allows companies to collect user-generated content (UGC) data. The use of big data analytics tools allows them to analyze data and gain customers insight effectively and efficiently [7].

A. User-Generated Content

Content is considered UGC when the content is published on a public, accessible website or on a social networking website accessible by a selected group of people. UGC offers opportunities and challenges for the company. In fact, the ability of the company to respond to these challenges may depend on the purpose of the contribution of the user. UGC represents an important paradigm shift in which companies must be willing to give up certain strengths that are traditionally tightly controlled by companies to customers [8]. The main purpose of UGC is product promotion because user-generated content usually shows strengths/weaknesses related to a product or brand and is designed to encourage mouth-to-mouth activity [9]. UGC can function in e-commerce as a new form of word-of-mouth for its products / services or providers [10].

B. Exploring UGC with Text Mining

The Text Mining technique can be used for exploring insights from large number of UGC reviews. It enables business person or application developers to identify application problems in a more detailed way by discovering users' emotions or perceptions from their reviews. Sentiment Analysis is usually chosen for exploring the sentiment using a set of textual data. This model determines whether a text contains positive, negative or neutral polarization. It has becoming very popular in the "customer voice" type of application [11]. The basic tasks of Sentiment Analysis models relate to classifying texts, for example, subjective (opinion) or objective (facts) classification or categorization, using machine learning or natural language process (NLP) techniques.

In addition to the use of sentiment analysis method, Topic Modeling method is necessary to identify the main topics of the reviews, our understanding of users ' perception of mobile application quality has been enhanced. So in its application, one will be able to distinguish what the main problems keywords are. In other words, Topic Modeling is a technique of text mining to find and track word groups in a document [12].

C. Sentiment Analysis

Sentiment analysis plays a large role in the field of research carried out by many researchers. Likewise, with application user reviews, application reviews usually contain positive and negative emotions of users [5]. Therefore, this study uses sentiment analysis to see the emotions of application users. With the sentiment analysis can detect the contextual patterns that exist in a text. In exploring user reviews, we use a machine learning based approach because this approach has a high degree of accuracy in classifying a text [13]. And for classifying the text, we use Naïve Bayes because it is a good algorithm for classifying problems regarding service quality [14]. With the classification, we can solve problems that occur in services [15].

In the technique, sentiment analysis classifies text into two classifications, namely positive and negative. Data on existing reviews must be trained in order to get more fit results in machine learning. For example, user satisfaction will include positive sentiments, while reviews of errors in the application will contain negative sentiment.

D. Topic Modeling

Application developers need to know clearly what topics are often discussed by users to determine areas to improve. For example, entities in a topic group might be important evidences to consider. Conclusion can be made accordingly.

Topic modeling can be used to see the main topics in user reviews. The practice is to identify hidden event patterns from a set of words using word distribution in a set of documents [16]. The output is a set of topics consisting of groups of words from a document according to certain patterns [17]. For each document in the corpus, topic modeling is also very useful in identifying hidden subjects and themes based on related words in an event. Furthermore, topic modeling is a good way to "let the text talk" because the identified topics are not dependent on individual perspectives or experiences [18].

Number of topics were chosen among a range of optimal numbers of topic groups. These numbers was acquired using empirical means using 4 metrics. Both maximization and minimization techniques are available. The first maximization metric is Arun2010 to observe divergence values in terms of symmetric KL-Divergence of salient distributions. The second maximization metric is the CaoJuan2009 method in selecting best LDA models based on density. Two metrics in minimimization techniques are the Griffiths2004 which uses Gibbs sampling algorithm and the Perplexity (Deveaud2014) to evaluate probabilistics model to measure the log-likelihood of a held-out test set [19]. The optimal range is situated between the number of topics at the intersection of the Arun2010 plot and CaoJuan2009 plot for minimization, and the number of topics at the intersection of Griffiths2004 plot and Deveaud2014 plot for maximization [20].

III. RESEARCH DESIGN AND METHODOLOGY

A. Research Question

Our objective was to analyze perceived quality towards tourism mobile applications using Sentiment Analysis and Topic Modeling methods. Naïve Bayes was selected as the classifier for sentiment analysis and Latent Dirichlet Allocation (LDA) as the modeler of the topics. We aimed for several outcomes:

1. The accuracy of Sentiment Analysis model to classify both Traveloka and Tiket.com users' sentiments based on Naïve Bayes algorithm
2. Identification of sentiments toward large numbers of Traveloka and Tiket.com apps reviews in Google Play Store
3. Generation of topic models for each quality dimensions

A user review may contain negative, or positive sentiment. For an example, "Thank you Tiket.com, this app helps me arrange a field trip easier" contains a positive sentiment, while "I only want to know the price of a boat ticket but it's really difficult" contains a negative sentiment. The machine will do testing based on the data learned so that testing data will appear with the level of how accurate the sentiment analysis.

B. Research Method

To answer the research question above, we carry out data collection for further cleaning so that the data to be processed is truly relevant data which will then be explained by the research method in fig. 1.

We managed to collect data from Google Play Store for Traveloka and Tiket.com reviews. Data were collected with timestamps in ten months period from January 1st, 2018 to October 24th, 2018 with a total of 12,311 user reviews. Newly collected data is a raw data. Raw data is cleaned by removing irrelevant data such as advertisements, spam, or simply redundant messages. Training data quality will affect sentiment analysis model's accuracy significantly. Further pre-processing data involved converting unstructured data into structured one and eliminating unnecessary data variables. Data pre-processing was done in three stages as shown in Fig. 2.

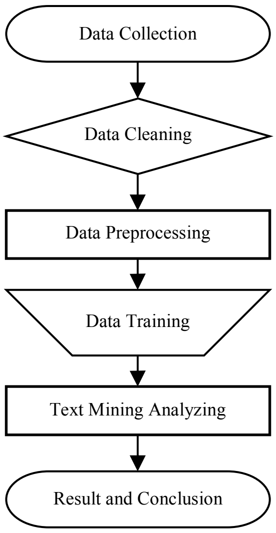

Fig. 1. The research workflow

Cleaned data are labelled according to positive-negative sentiment and quality dimensions. A ratio of 70:30 is used to split collected data into training and testing sets.

Tokenization is a process to slice reviews into individuals so that the stopwords filter can be used to filter out words that do not have a significant effect to a sentiment polarity such as "I", "was", and "them". The next process called Stemming provide prefixes and suffixes removal mechanism to get a basic-words bag (Bag of Words – BOW).

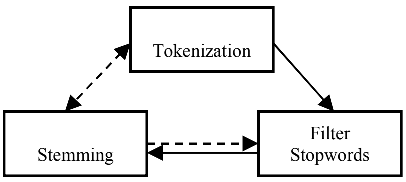

Fig. 2. Preprocessing flow

Sentiment Analysis and Topic Modelling were conducted in the 5th steps. Both will give different result types. Naïve Bayes based Sentiment Analysis outputs a predictive classification model while Topic Modelling using LDA method gives an estimation model of topics clustering. We used Naïve Bayes Classifier (NBC) algorithm for classifying customers' reviews data and classifying them according to the six dimensions of MappSql, that are customization, service recovery, functionality, design, fulfillment, and assurance. We ran an R script in RStudio to generate models of topics and to visualize the results. Several packages are manually installed such as tidyverse, tidytext, topicmodels, tm, SnowballC, etc. Classification model was generated and evaluated in Rapidminer Studio.

C. Evaluation Metrics

Our classification model performance is evaluated by using confusion matrix with the following formula:

$$\text{Accuracy} = \frac{\text{TP + FN}}{TP + FN + FP + FN} \quad (1)$$

TP (true positive) and TN (true negative) are numbers of true positive and negative predicted labels. Whereas FP (false positive) and FN (false negative) are numbers of the model's false predictions.

Precision and recall values can be calculated using the following metrics:

$$\text{Precision} = \frac{\text{TP}}{TP + FP} \quad \text{Recall} = \frac{\text{TP}}{TP + FN} \quad (2)$$

Accuracy measures the correctness of the classification models in predicting labels. On the other part, precision shows the ratio of correct prediction and total positive or negative predictions. Recall shows the ability of the model to recognize each members of positive or negative classes among a set of unlabelled data [21].

IV. RESULT AND ANALYSIS

Based on the values of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), the results of machine learning performance evaluation in text classification can be seen from accuracy, precision, and recall. Accuracy values describe how accurate the machine can classify data correctly. In other words, the value of accuracy is a comparison between number of correctly classified data and the number of overall data. The measurement of the text classification performance model can be seen in Table I and Table II.

TABLE I. EVALUATION AND ACCURATION RESULT OF TRAVELOKA

Accuracy: 88.00% +/- 2.95% (micro average: 88.00%)

	True Positif (TP)	True Negatif (TN)	Class Precision
Pred. Positive	848	47	94.75%
Pred. Negative	102	245	70.61%
Class Recall	89.26%	83.90%	

TABLE II. EVALUATION AND ACCURATION RESULT OF TIKET.COM

Accuracy: 91.06% +/- 2.58% (micro average: 91.06%)

	True Positif (TP)	True Negatif (TN)	Class Precision
Pred. Positive	1439	97	93.68%
Pred. Negative	81	373	82.16%
Class Recall	94.67%	79.36%	

Can be seen from Table I and II, Traveloka has true positive (TP) and true negative (TN) predicted labels value of 848 and 245 data. Which the classifiers count it to false predicted labels value of 102 and 47 data for false positive (FP) and false negative (FN). Whereas Tiket.com has TP, TN, FP, and FN value of 1439, 373, 81, and 97 data.

Based on the calculation of TP, TN, FP, and FN. Traveloka has a classification accuracy value of 88% and 91.06% for Tiket.com. It means Naïve Bayes Classifier has a very good performance. This is proven by the results of Traveloka text classification accuracy values that have a value of 88% and are categorized as Good, and Tiket.com entered into the Excellent category because it has an accuracy value of 91.06%.

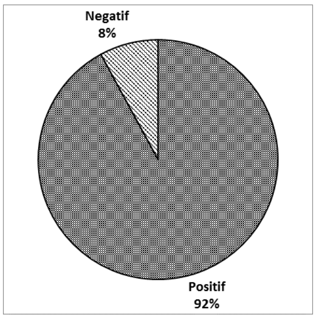

Fig. 3. Traveloka Sentiment Classification

During the last ten months, can be seen in Fig. 3 Traveloka has 92% positive and 8% negative sentiment of users' application. This shows while using the, users' already feels satisfied with the application service, so that they give a positive response in the form of positive reviews.

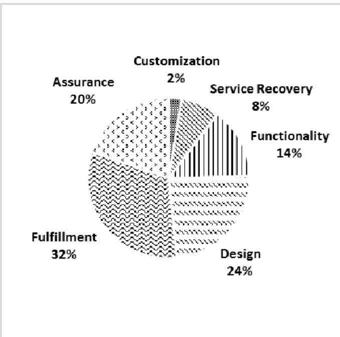

Fig. 4. Traveloka MappSql Classification

Fig. 4 shown classification of the MappSql's dimension of Traveloka. Fulfillment are the most often discussed compared to other dimensions, i.e. 32%. Observations state that Traveloka is an application that fulfills its service promises, i.e. providing fast and easy services, and the availability of tickets that always available. As for the other dimensions, Traveloka has a classification of 24% for Design, 20% for Assurance, 14% for Functionality, 8% for Service Recovery, and 2% for Customization.

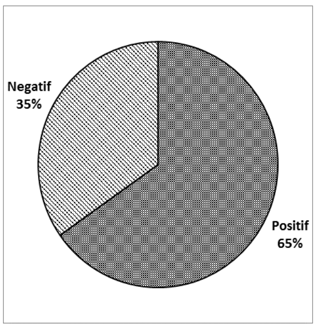

Fig. 5. Tiket.com Sentiment Classification

Tiket.com has 65% positive and 35% negative sentiment. This shows that while using the application, users already feel quite satisfied with the application service so that 65% users' give a positive response.

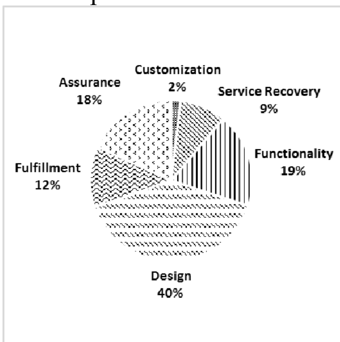

Fig. 6. Tiket.com MappSql Classification

As seen in Fig. 6. Design are the most often discussed from the other five dimensions, i.e. 40%. Tiket.com has an attractive application design and user friendly. While in other dimensions, Tiket.com has a classification of 19% for Functionality, 18% for Assurance, 12% for Fulfillment, 9% for Service Recovery, and 2% for Customization dimensions

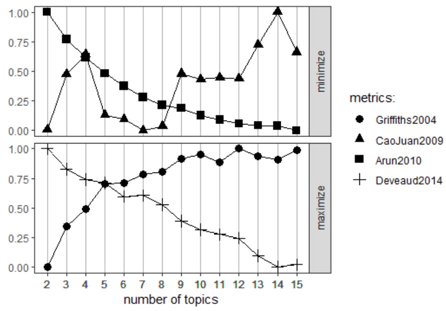

Fig. 7. Optimal Number of Topics for LDA Model

Topic modellings are done in RStudio entirely. Each topic models are generated in under 1 second using a laptop computer using 6th generation of Core I5 processors, and 8GB of RAM. Optimal numbers of topic groups are between 4 and 9 based on maximization and minimization techniques. We chose 5 for the sake of simplicity of discussion.

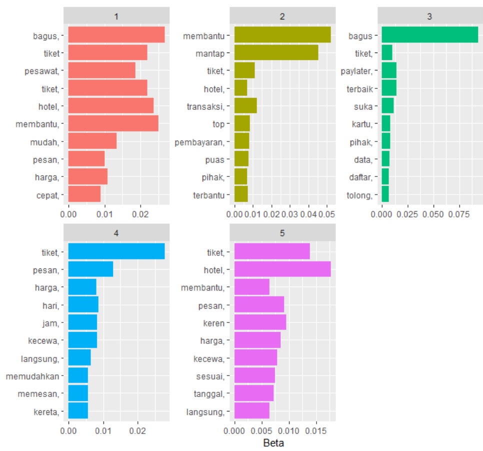

Fig. 8. Topic Modeling for Complete Reviews for Traveloka Case

Fig. 8 shows the results of the Traveloka's topic modeling. The number on the x-axis shows how often the word appears on a topic. Bigger Beta values indicate higher appearance frequencies of particular words in a single topic group. All the topic discussed was reflected in the words that appearing of the topics above and have been seen in Fig. 8. The 1st topic contain words such as *bagus*, *tiket*, *pesawat*, *tiket*, *hotel*, *membantu*, *mudah*, *pesan*, *harga*, and *cepat*. Adjective words specify abstract levels of customer satisfaction (*bagus, mudah, membantu,* and *cepat*) in relation to possible subjects such as *tiket, hotel,* and *pesawat*. The topics group may also implies important activities.

The 2nd topic caters payment activites for tickets and hotels. Users' satisfactions on its availability seems to have reached high level of satisfaction reflected by *mantap, top, puas,* and *terbantu*. On the 3rd topic discussed about transactions in the application. Many users dissatisfied about it because they could not use the credit card during the payment process. Reviews regarding PayLater's new features also contain negative sentiments. Nonetheless, some users expressed satisfaction with the PayLater's feature. Most positive sentiments came from reviews related to easy to use transaction system.

The 4th topic discusses about customers having dissatisfaction with application system performance. User feels disappointed with the availability of ticket wich sold out quickly during certain days, such as holidays. Applications also has a bad server performance on the high traffic visitors The 5th topic contains users' negative perceptions related to complaints management, pricing scheme and lowest price guarantee compared to other booking sites.

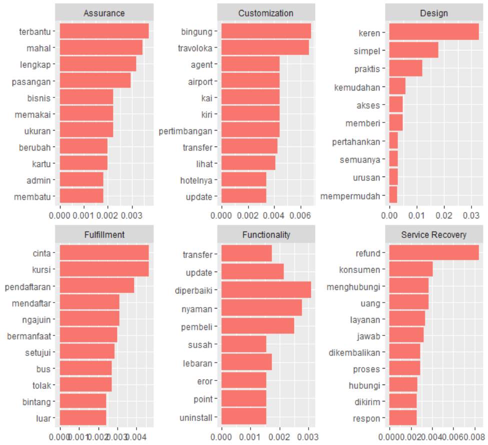

Fig. 9. Topic Modeling for Traveloka's MappSql Dimensions

Fig. 9 shows the topic modeling for Traveloka's MappSql. Most of the dimensional topics shows positive sentiments. In terms of Assurance's dimension, Traveloka has a good image because it has fulfilled the service promises. Customization's dimension discussed about user requests for Traveloka to add and complete in-app information regarding seating on the train and terminal at the airport. And to add hours of online transfers such as at night and clarify information about virtual accounts. Design's dimension discussed about the application already has a good design. Topics that exist in the Fulfillment's dimension shows customer appreciation with PayLater's features. Service Recovery dimension shows users thankfulness for customer services' good responses in serving customer complaints.

In contrast to other dimensions, Functionality dimension show negativism about application compatibility issues in several smartphone types or brands, causing errors that force users to uninstall.

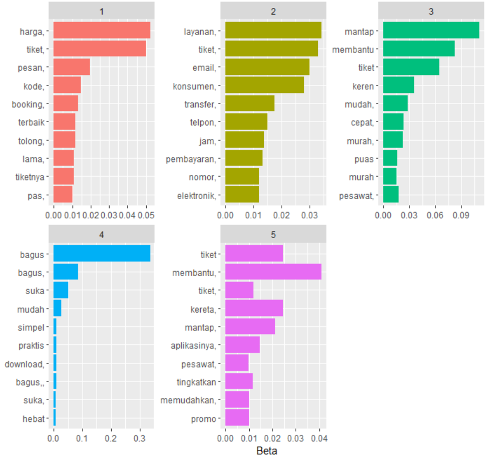

Fig. 10. Topic Modeling for Complete Reviews for Tiket.com Case

Optimal numbers of topic groups for Tiket.com case are between 5 and 10. We also chose 5 for the sake of simplicity of discussion. The 1st topic shows the weaknesses of the application system problems related to electronic ticket issuance. The 2nd topic discussed about low responsiveness of customer services in processing complaints.

The 3rd topic shows user satisfaction to the application user-friendliness and the facilitation functionality they had by using the application. The 4th topic discussed about application design. Users consider the design of Tiket.com's application is quite good as shown by the high frequency of word "*bagus*" appearance. The 5th topic discussed about satisfaction of users about performance of application services.

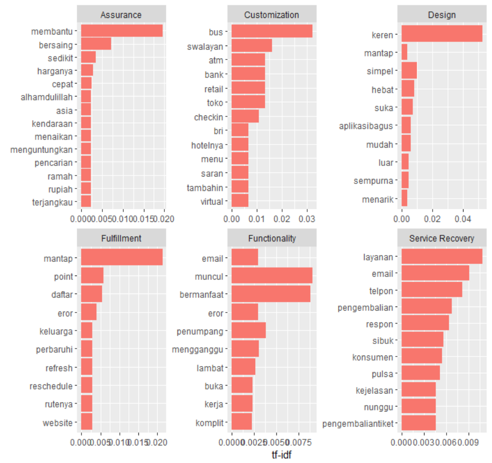

Fig. 11. Topic Modeling for Tiket.com's MappSql Dimensions

Seen in Fig. 11, for the dimension of Assurance, application has fulfilled the promise of service delivery and provided the best solution for customers. The topics in the Customization dimension discussed about the flexibility of payment. Tiket.com should add virtual account payment options in order to reach all banks and more payment options through retail stores. Design's dimension discussed about application's good design.

Fulfillment's dimension contains user dissatisfaction towards ticket information renewal. In terms of Functionality, user's discussed about performance of application systems that often erroneous, slow, and inaccessible. Electronic tickets status not showing up makes users feel disappointed with the performance of the application system. Service Recovery's dimension discussed about customer service department's bad responses in serving customer complaints.

V. CONCLUSION

Large numbers of UGC data gathered from social media enables data science practitioners to apply text mining techniques to reveal users' perceived quality through sentiments and popular topics towards several quality dimensions.

Proper data pre-processing activities including data cleaning processes are required to achieve more than 80% Naïve Bayes classifier accuracy. Best accuracy obtained for Traveloka case was 88% and 91.06 % for Tiket.com case. We conclude that Naïve Bayes classifier is reliable for classifying users' sentiment toward MappSql quality dimensions from textual data.

Aggregation of sentiments numbers can be used to compare proportions of positive and negative sentiment. Traveloka has 92% positive sentiment. Whereas Tiket.com has only 65% positive sentiment. Tiket.com has 35% negative sentiment instead of 8% as what Traveloka has. This translates to higher overall users' satisfaction in Traveloka apps usage compared to satisfaction in Tiket.com apps usage.

In terms of MappSql's dimension, Fulfillment dominates among other five dimensions in Traveloka case by 32%. Whereas Tiket.com case shows Design dimension is the most important aspect having 40% portion. Both OTA providers have different top priorities to consider in improving their MappSql qualities.

Each sets of dimension-related reviews also contain specific topics related to quality dimension's attributes or values such as the availability, flexibility, payment methods, transaction methods, functionality, or user interface design. These can be improvement focus areas. OTAs can tune their business features based on topics and related positive and negative sentiments using both factual and actual data from large number of reviews.

Reviews may be gathered from websites and mobile app. Sentiment analysis and Topic Modelling towards MappSql processes can be implemented for both website and mobile app qualities measurement, thus unifying and simplifying business improvement tasks. This will leads to better management for increasing user satisfaction where seamless integrations in multi-platform business is crucial.

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