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Analysis of Online Travel Agent Marketing Strategies on Social Media Content Using Sentiment Analysis and Social Network Analysis

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Abstract

The growth and development of the internet users have given Indonesia an opportunity to develop internet-based services, such as online travel agents (OTA). Along with this OTA development, conventional travel agents were declining. Many conventional travel agents have decided to switch to online travel agents. The emergence of new OTAs has also made OTAs competition more challenging. Thus, a lesson learned from the market leader OTA is expected to help new OTAs surviving the competition. This research uses the sentiment analysis method to understand consumers' perceptions towards OTA and uses the social network analysis method to recognize actors who play significant roles in the travel agent business network. Lastly, the marketing strategies of the major and well-known OTAs perceived by online consumers was analyzed. Using the data collected from three major OTAs social media network (i.e., Traveloka, Tiket, and Booking), it was found that the general impression of consumers towards OTA is a positive sentiment. Furthermore, each key actor for each OTAs can be recognized. Lastly, marketing strategies can be proposed, namely by providing the complete product offerings, provide competitive price, creating special promos for consumers, promotion to be carried out on all social media using Bahasa Indonesia, and make the products offered available throughout Indonesia and can be used by everyone, especially travelers.

Keywords: Sentiment Analysis, Social Network Analysis, Online Marketing, Twitter

1. INTRODUCTION

The growth and increase of internet users make Indonesia an opportunity for developing the online travel agent (OTA) business. In 2020, more than 100 travel agents were closed during COVID-19 pandemic because of the decline in sales, which forced those travel agents who want to survive to cope with the change and embrace a new business model based on technology [1]. Conventional travel agents that don't utilize the internet in their business model can't compete in the market. Thus, conventional travel agents have decided to switch to become online

travel agents [2]. Online Travel Agent (OTA) is a travel agent that acts as an online promotional and sales media through a website or application created and managed to distribute and facilitate bookings to tourism business providers [3]. OTA business model provide several benefits, such as: convenience in buying decision making process, getting product or service information in shorter time, quick response, can choose according to customer's want and condition, can reduce printing and postage costs (physical promotions), and can reduce labor costs [4]. The well-known OTAs in Indonesia in 2023, according to Databoks (databoks.katadata.co.id), are Traveloka, Tiket.com, and Booking.com.

The emergence of new OTAs also means the competition between OTA companies is increasing. This competition makes it increasingly challenging for companies to build consumer loyalty because consumer demands are increasingly higher along with the convenience that is obtained [5]. This condition can result in losses in sales if the company does not maintain and increase its customers. Therefore, customer engagement and social media awareness have made OTAs need to increase their marketing efforts. This situation necessitates OTAs to innovate their business strategies.

Along with the development of internet users in Indonesia, the number of social media users has also increased. Social media is an effective marketing tool with several purposes [6], for example to express opinions is Twitter (now X), to be able to connect in a large network is Facebook, to be able to share expertise is LinkedIn, and to be able to express oneself is Instagram and Pinterest. Twitter social media has the potential to disseminate good information with a greater amount of information dissemination compared to Google Plus and Facebook [7]. The number of Twitter users in Indonesia increases every year. Therefore, Twitter social media is considered as social media that can be used to collect information from OTA consumers. Through this social media, content created by users about OTA services can be publicly accessed by other social media users. This content can be categorized into positive, negative, or neutral reviews.

Sentiment analysis is one of the methods used to gain general information about consumer emotions when using or purchasing OTA services. Sentiment analysis was carried out during the lockdown policy in India, using several techniques [8]. Another application of sentiment analysis was in analyzing film reviews [9]. It is also used to analyze e-commerce platform in China using lexicon based techniques and deep learning techniques [10]. In Indonesia, social network analysis was used to determine the marketing strategy success on Shopee and Tokopedia [11]. This method was also used to analyze sentiment values in reviews of the Traveloka and Tiket applications [12]. The analysis applied to research data from Twitter has been done before [13]14]. Apart from that, social network analysis can be used in OTA development to disseminate information [15]. Thus, these two methods can be used to support the design of marketing strategies in developing OTAs. Therefore,

this research aims to provide a general overview of consumer sentiment in using online travel agents based on reviews on Twitter social media, a recognition of the influential actors in the social media information network using the keywords for each OTA (i.e., @traveloka, @tiket, and @bookingcom), and an analysis of the marketing strategies used by major OTAs using marketing mix approach.

2. METHODS

The flow of this research can be seen in Figure 1. Data (i.e. text) is collected on Twitter and then used to conduct Sentiment Analysis and Social Network Analysis. The content extracted from the text mining is used in analyzing the marketing strategies for OTAs. The details are in the following sub-chapters.

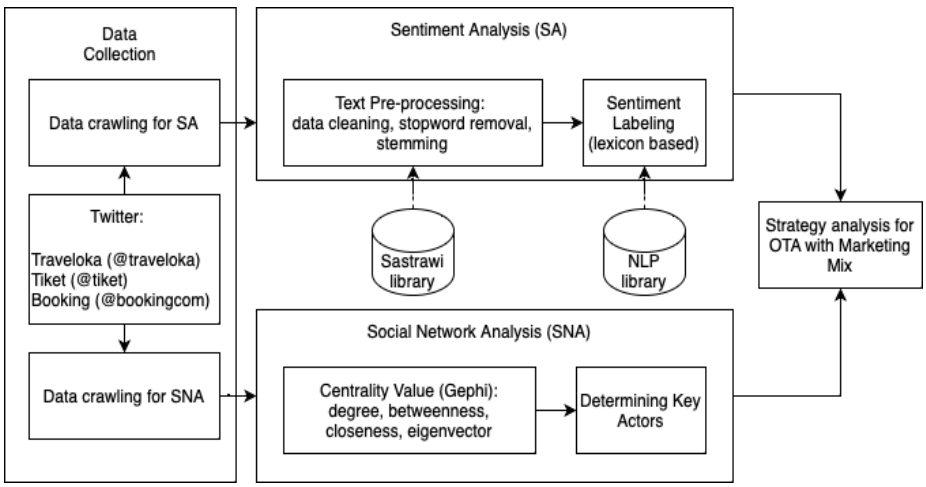

Figure 1. Research flow

2.1 Data Collection

The research data was taken from user-generated content via Twitter (now X). User Generated Content (UGC) is data from content that can generally be seen by other social media users and is created by people who are not professionals [16]. Thus, UGC is content created by social media users themselves. Twitter users' tweets that have been collected contain the important topics discussed regarding three OTA companies, namely @traveloka, @tiket, and @bookingcom. Data is retrieved through data crawling, which is then downloaded into a csv file (see Figure 2). Through data crawling, 2,073 tweets with the keyword @traveloka, 1,967 tweets with the keyword @tiket, and 492 tweets for @bookingcom were found on Twitter posts from early January 2023. This data will then be processed using the sentiment analysis method.

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Figure 2. Data crawling result (.csv)

The choice of this date was made because there are large events that use online travel agents to provide concert tickets to lodging for concert ticket buyers. On Traveloka's official website, there are 23 major concert events until June 2023 that use Traveloka to provide tickets. So, the selection of this date is due to important events or events during this period that can affect user sentiment and interaction on Twitter. Then, the data crawling for social network analysis is carried out also in the early 2023 but not quite the same period with the previous collection due to some restriction caused by new Twitter policy. The data obtained is then processed to obtain influential actors in the network. The processed data was also used later to gather insights for the purpose of designing the marketing mix.

2.3. Sentiment Analysis (Lexicon-Based)

In the data obtained through crawling, the *user/screen_name* and *full_text columns* are required for this sentiment analysis. Sentiment Analysis is a useful process for finding out the general overview expressed by consumers, the results of which can provide the views or moods of consumers spread across the network [17]. In this process, there is text pre-processing; this process is carried out to remove irrelevant content and collect related terms to reduce data sparsity [18]. Data pre-processing was done through several stages: data cleaning (case folding, tokenizing, spelling normalization), stopword removal, and stemming [19]. Data cleaning is carried out to remove uppercase to lowercase letters, remove unnecessary characters, and delete URLs, image media, and videos. Then, the stemming is in the form of reducing inflected words in Indonesian to their basic word forms. Next, stopword removal, which refers to the arrangement of Indonesian stopwords from the Sastrawi library and slang stopwords. The data that has been stemmed is then subjected to sentiment labeling by giving positive, negative, and neutral labels. Dictionary for emotional meaning of words (from NLP library) was used as the base for labelling (lexicon-based sentiment) [10]. Scores are assigned to words based on their emotional weight, and then added up to get an overall sentiment score.

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2.4. Social Network Analysis

Social Network Analysis (SNA) is a method used to study the relationship between one entity and another entity which is assisted by graph theory, so that an overview of the smallest relationships in the network is obtained [15]. The data needed is *source* and *target*. Through this method, centrality values can be obtained, of which there are four centralities, namely *degree centrality* (identifying actors who have many connections), *betweenness centrality* (identifying the role of actors who are the link between interactions), *closeness centrality* (identifying the average distance or closeness of a node to other nodes in the network), and *eigenvector centrality* (finding actors who have relationships with other influential actors) [20]. The following is the formula for each centrality:

a. Degree Centrality

$$C_D(n_i) = d_{(ni)} \quad (1)$$

Information:
$d_{(ni)}$= the number of interactions that occur at node n_i with other nodes in one network

b. Betweenness Centrality

$$C_B(n_i) = \sum \frac{g_{jk(n_i)}}{g_{jk}} \quad (2)$$

Information:
$g_{jk}(n_i)$ = number of shortest paths from node j to node k that pass through node i
g_{jk} = number of shortest paths between 2 nodes in a network

c. Closeness Centrality

$$C_c(n_i) = \left[\frac{N-1}{\sum d(n_i,n_j)}\right] \quad (3)$$

Information:
N = number of nodes in the network
$d(n_i, n_j)$ = number of shortest paths connecting node n_i and node n_j

d. Eigenvector Centrality

$$C_i(\beta) = \Sigma (\alpha + \beta_{cj}) A_{ji} \quad (4)$$

$$C_i(\beta) = \alpha (I - \beta A)^{-1} A1 \quad (5)$$

Information:
α = normalization constant or vector scale
β = the number of nodes that have a centrality weight in nodes that also have a high centrality value.

2.5. Marketing Mix (4P)

Marketing Mix is a marketing tool used by companies to achieve their marketing goals, in this case the marketing mix consists of product, price, place and promotion [21,22]. *Product* is a process concept that provides benefits to consumers, *price* is the price that can be considered when deciding on a transaction, *place* is the location offered by the company, then *promotion* is an aspect of reaching consumers. The insights found through analyzing the content, is then grouped into each aspect. Using this collection of insights gathered from three well-known OTAs, new OTAs hopefully can learn what strategy that they can used for themselves.

3. RESULTS AND DISCUSSION

3.1 OTA Sentiment Analysis

The sentiment analysis results of online travel agent Traveloka have a positive sentiment of 1146 tweets from the total 1882 tweets, which means they have a positive sentiment percentage of 61%, then for the negative sentiment, the percentage is 11%, and for neutral sentiment, it is 28% of the total (see Table 1 for all OTA sentiment analysis results).

Table 1. OTA Sentiment Analysis Results

	Positive	Negative	Neutral
Traveloka	1146	202	534
Tiket	1187	145	481
Booking	232	140	99

Tiket.com has a positive sentiment value with 1187 tweets with a total of 1813 tweets processed. Therefore, the percentage of positive sentiment is 65%, negative sentiment percentage is 8% and for neutral sentiment is 27%. Furthermore, Booking.com received positive sentiment as many as 232 tweets with a percentage of 49% of the total, 30% for negative sentiment, and 21% for neutral sentiment. Therefore, most of the sentiments for each OTA is positive. These results prove that the activity of OTAs in social media is generally well-received. Thus, we can use the marketing content to extract and analyze the value proposed or strategy implemented by the three OTAs in social media.

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Sentiment data produces word associations for each existing OTA. Word associations are divided into positive, neutral and negative sentiment word associations, as the visualization can be seen in Figures 3, 4 and 5.

Figure 3. Positive Sentiment Word Association

Figure 4. Neutral Sentiment Word Association

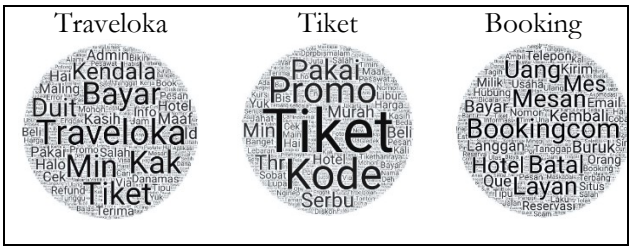

Figure 5. Negative Sentiment Word Association

While positive sentiment is dominant in all OTAs, Tiket.com has a higher positive image compared to other OTAs in terms of percentage. What influences this sentiment is that the words or tweets created or interacted with the official @tiket account have more positive value. The weight of the words used is higher. See Table 2 for the labelling results.

Table 2. Example of OTA Sentiment Labeling Results

Online Travel Agent	Stemmed words (Indonesia)	Compound	Sentiment
Traveloka	*aduh weekday crazy kena macet mending rencana libur weekend pakai promo crazy sale jakarta discount tanggal juni run*	-0.0516	negative

Online Travel Agent	Stemmed words (Indonesia)	Compound	Sentiment
Tiket	*ekspresi macet klakson bikin stress*	-0.4215	negative
	reply tag teman ikut challenge anyway tonton spider man across the spider verse bioskop	0.6808	positive
	join group hadiah juta rupiah hadiah spesial banget sobat tiket follow mention tiket ajak orang teman join grup facebook like reply screenshot bukti join grup	0.9595	positive
	join group libur murah meriah join facebook group jamin sesal sobat tiket promo eksklusif khusus member buru join group	0.3895	positive
	the house tour hotel uphill terus sersan bajuri cihideung kecamatan parongpong kabupaten bandung barat hotel milik kamar unik bentuk kabin instagramable banget kamar bathtub pandang langsung alam bandung	0.0000	neutral
Booking	*sayang lepas beban kerja lidi selesai capai tingkat terima kasih sabar mohon maaf ketidanyamanan salam*	0.2263	positive
	kemasi lemari pakaian fedora beli	0.0000	neutral
	terbang jam pagi kopi wajib	0.0000	neutral

3.2 OTA Social Network Analysis

This data cleaning is carried out to obtain the data needed by the Gephi application. The data needed by this application is *source* and *target*. The source is the tweet creator and the target is the person who interacted with the tweet. The connection between these many sources and targets creates the network. The visualization of the network can be seen in Figure 6. The interactions that occur in the network is between the official accounts of three online travel agents and the personal accounts of consumers.

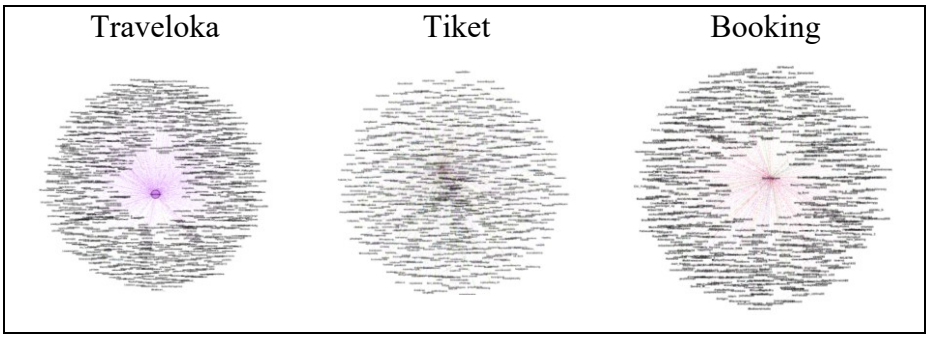

Figure 6. SNA visualization of OTAs

Then, using a statistical overview with the Gephi application, centrality measurement results were obtained. The results can be seen in Table 3, 4, and 5. Through centrality results, it is possible to identify each key actor who is most influential in the network of each online travel agent.

Table 3. Traveloka centrality results

No	Degree Centrality		Betweenness Centrality	
	Account	**Weight**	**Account**	**Weight**
1	@traveloka	576	@traveloka	9627
2	@kimmeowgyu	5	@kimmeowgyu	923
3	@nabilaaapr13	5	@melindahasibuan	638
4	@jerryalamsyah23	5	@navilafirdaus2	636
5	@Tomsky1892	5	@Jaebubzz	633

No	Closeness Centrality		Eigenvector Centrality	
	Account	**Weight**	**Account**	**Weight**
1	@catsedih	1	@traveloka	1.0
2	@onewarsone	1	@Yayaopukis	0.175
3	@nailanaee	1	@pryekstgn	0.175
4	@shycham_	1	@Tomsky1892	0.161
5	@pieceofcabbage	1	@kamusiapayaya	0.161

Table 3 shows that three key actors were found in the keyword @traveloka, namely accounts with the usernames @traveloka, @kimmeowgyu, and @nabilaaapr13. The @traveloka account, which is the official account for Traveloka, itself is the key actor, because this account has the highest distribution potential with the highest number of likes being 160 thousand likes and replies of 838 accounts. Next, the @kimmeowgyu account also has potential for information

dissemination with 3,200 tweets likes and 60 replies. Tweets posted on this account describe the promos that are obtained, thus attracting other accounts to view them. The @nabilaaapr13 account received 61 replies with tweets describing complaints about payments made, so consumers were interested in seeing the resolution made by Traveloka.

Table 4. Tiket centrality results

No	Degree Centrality		Betweenness Centrality	
	Account	Weight	Account	Weight
1	@ticket	476	@ticket	68356
2	@muhajirabar	8	@muhajirabar	751
3	@nabilaaapr13	7	@septiiyaann	550
4	@fijaei	5	@higendish	545
5	@septiiyaann	5	@fijaei	523

No	Closeness Centrality		Eigenvector Centrality	
	Account	Weight	Account	Weight
1	@septiiyaann	1	@ticket	1.0
2	@pureshafira	1	@alaziess	0.173
3	@onlynull	1	@nabilaaapr13	0.161
4	@floemiehaechan	1	@kantongrejeki	0.161
5	@cistinitsic	1	@ZawnZzun	0.159

As for the keyword @tiket, three top key actors are the one with the account usernames @tiket, @muhajirabar, and @nabilaaapr13 (see Table 4). Here, the official account of the travel agent is also the main actor in addition to influencing the number of followers, as well as the replies to every tweet made. Second highest is @muhajirabar account, which has several replies mentioning it in tweets complaining about hotel bookings. This complaint was resolved well by Tiket, thereby generating consumer interest in seeing the tweet. The @nabilaaapr13 account is also a key actor due to complaints about the payments that he/she made. This tweet resulted in 487 quote tweets. Thus, information about this complaint spread very quickly.

Table 5. Booking centrality results

No	Degree Centrality		Betweenness Centrality	
	Account	Weight	Account	Weight
1	@bookingcom	412	@bookingcom	47414.5
2	@irishacw	5	@JP19711971	674.0

No	Degree Centrality		Betweenness Centrality	
	Account	Weight	Account	Weight
3	@devbarad2009	5	@devbarad2009	644.0
4	@JP19711971	4	@saaa240	456.0
5	@pilibarb	4	@irishacw	420.0

No	Closeness Centrality		Eigenvector Centrality	
	Account	Weight	Account	Weight
1	@shiftyarrowfrog	1	@bookingcom	1.0
2	@ratu_noviy95898	1	@w1971401	0.248
3	@ravindrasinghyd	1	@Recuenco	0.225
4	@flowerssssp	1	@Ryann75	0.220
5	@sbooth29	1	@Jennmiester	0.220

Lastly, the keyword @bookingcom produces three key actors, namely @bookingcom, @irishacw, and @devbarad2009 (see Table 5). The official account @bookingcom is also the main actor in the network, getting the most quote retweets with 129 thousand. For the @irishacw account, these are tweets about her/his complaints about the refund process, which she/he never received. This issue received 8000 retweets and 4 tweets in reply. Then, @devbarad2009 also had the same complaint, namely about refunds for canceling a trip. These tweets got 6000 quote retweets and 5 replies to tweets.

While positive sentiments fill most of the tweets, consumer complaints can potentially generate many replies and retweets. A successful handling of complaints can lead to positive reviews, as the other way around. Thus, OTAs need to be careful in handling it. Meanwhile, there are key actors (i.e., @nabilaaapr13) that can potentially present in different OTA networks. They can also become an actor that has many connections or have a relationship with other influential actors. Thus, recognizing this actor and give appropriate treatment to them may boost the sentiments of OTAs in social media.

3.3 OTA Marketing Strategy Analysis

By analyzing the content of the collected data, a marketing mix analysis is conducted for the three major OTA players. The result is shown in Table 6. This marketing mix shows the value propositions necessary in the OTA business model.

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Table 6. Marketing Mix Analysis

Criteria	Identification		
	Traveloka	**Tiket**	**Booking**
Product	There are hotel reservations, flight tickets, train tickets, bus tickets, concert tickets, children's playgrounds, car rentals, taxis, airport pick-up, flight insurance, discount packages, beauty and spa, flight and hotel packages*, and* tour packages.	There are hotel reservations, airline tickets, train tickets, bus tickets, concert tickets, children's playgrounds, car rental, airport pick-up, tour packages, spa and beauty, bus and shuttle tickets.	There are hotel reservations, airline tickets, car rentals, taxis, and entertainment.
Price	The price offered by Traveloka is not much different from other OTAs.	The price offered by Traveloka is not much different from other OTAs.	The price offered by Traveloka is not much different from other OTAs.
Place	The products offered in cover all over Indonesia.	The products offered in cover all over Indonesia.	The products offered in cover all over Indonesia.
Promotion	Promotions have been done on social media *twitter, facebook, youtube, via influencer* and also TV commercials. In addition, there are discounts offered by Traveloka.	Promotions have been done on social media *twitter, facebook, youtube, via influencer* and also TV commercials. However, for social media is not too active in promoting it can be seen from the number of *tweets* obtained.	Promotions have been done on social media *twitter, facebook, youtube, via influencer* and also TV commercials. However, bookingcom only has one social media for its promotion. Thus, on social media there is a mix use of foreign language.

In consumer perception, major OTAs seem to use the same strategies in many marketing aspects, with slight differences in other aspects. Therefore, marketing strategy design can be carried out by new and competing online travel agents in Indonesia by offering value that is relevant with the insights found from the three OTAs analyzed. The marketing strategy proposed are: (1) offering various products/services so that it can be a complete service provider; (2) provide competitive prices; (3) creating special promotions for consumers; (4) promotions are carried out on all social media using Indonesian language; and (5) make the products offered are available throughout Indonesia and can be used by everyone, especially travelers.

4. CONCLUSION

In conclusion, we can understand consumer sentiment in online travel agents by using sentiment analysis on major and well-known OTAs in Indonesia through social media (i.e., Twitter). In this study, most of the sentiment is positive, with the positive sentiment value from each OTA being 61% for Traveloka, 65% for Tiket, and 49% for Booking. Thus, the marketing content is suitable for further analysis to learn the best marketing strategies. Then, social network analysis can help to find the actors who were influential in the flow of information in the network. These influential social media accounts are found using *degree centrality* calculations, which aim to identify actors with many connections in the network. While most of the sentiment is positive, through investigating the interaction (i.e., re-tweets and replies) of the key actors in the social media network, we found that consumer complaints can potentially escalate the discussion on social media, though good handling of the complaints can then turn the reviews into positive sentiment. Furthermore, from insights found in the marketing mix of the major OTAs that consumers perceive, several marketing strategies are proposed, namely by providing the complete product offerings, providing competitive prices, creating special promos for consumers, promotions to be carried out on all social media using Bahasa Indonesia, and make the products offered available throughout Indonesia and can be used by everyone, especially travelers.

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