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# Recommendation agents and information sharing through social media for coronavirus outbreak

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ABSTRACT

The novel outbreak of coronavirus disease (COVID-19) was an unexpected event for tourism in the world as well as tourism in the Netherlands. In this situation, the travelers' decision-making for tourism destinations was heavily affected by this global event. Social media usage has played an essential role in travelers' decision-making and increased the awareness of travel-related risks from the COVID-19 outbreak. Online consumer media for the outbreak of COVID-19 has been a crucial source of information for travelers. In the current situation, tourists are using electronic word of mouth (eWOM) more and more for travel planning. Opinions provided by peer travelers for the outbreak of COVID-19 tend to reduce the possibility of poor decisions. Nevertheless, the increasing number of reviews per experience makes reading all feedback hard to make an informed decision. Accordingly, recommendation agents developed by machine learning techniques can be effective in the analysis of such social big data for the identification of useful patterns from the data, knowledge discovery, and real-time service recommendations. The current research aims to adopt a framework for the recommendation agents through topic modeling to uncover the most important dimensions of COVID-19 reviews in the Netherland forums in TripAdvisor. This study demonstrates how social networking websites and online reviews can be effective in unexpected events for travelers' decision making. We conclude with the implications of our study for future research and practice.

## 1. Introduction

The tourism and hospitality industries have been significantly affected by social media (e.g., websites and virtual communities) as

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well as travel-based online review emerging from consumer-generated media. The value of word-of-mouth generated by travelers on social media sites is an increasingly important antecedent in users' decision-making processes in tourism and hospitality contexts. Travel users in social media can produce, share and review and provide a suggestion about a hotel, an airline, and a restaurant, as well as share information about their personal experiences. Such users find travel-related reviews to be extremely valuable and credible (Yoo et al., 2009).

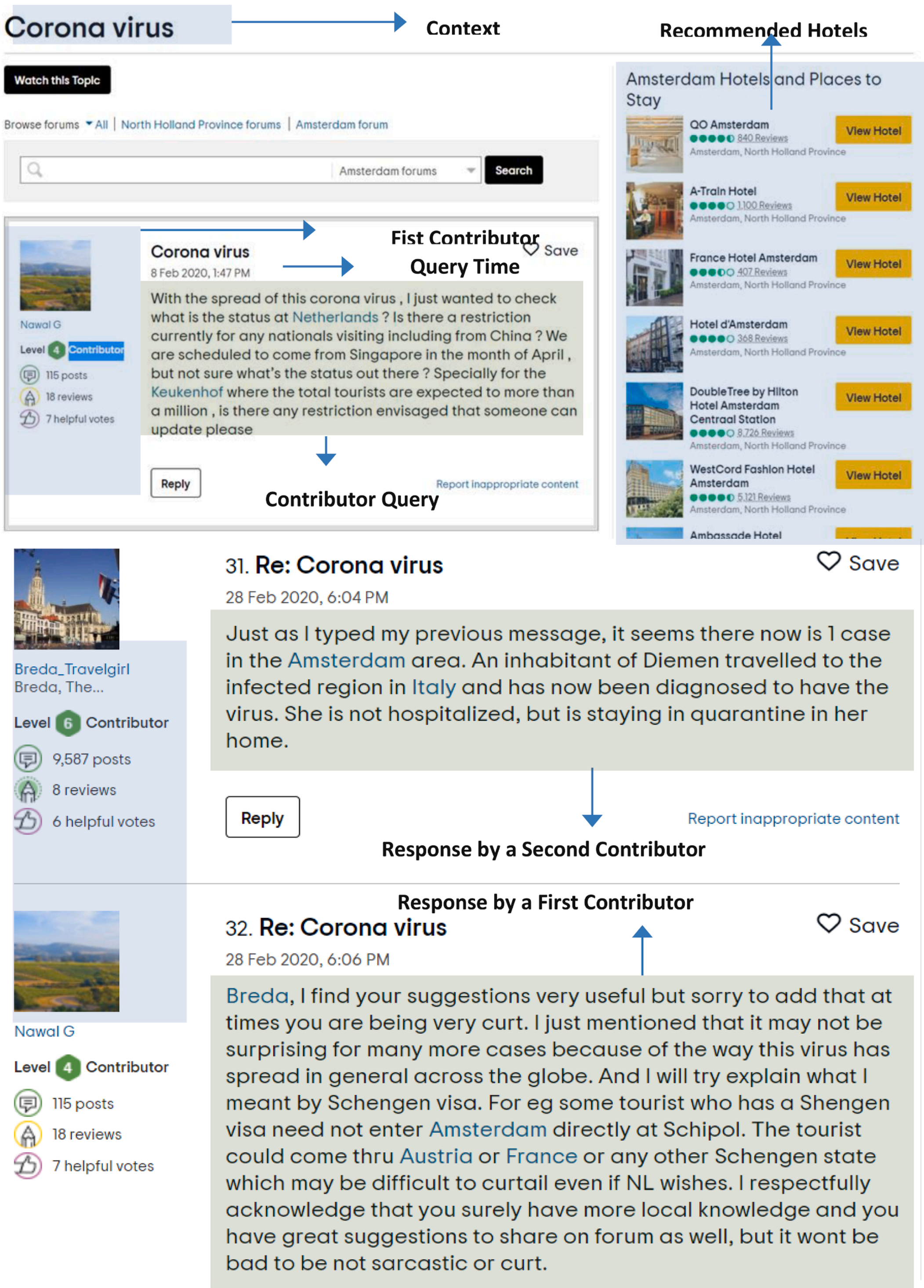


**Fig. 1.** The Amsterdam forum for coronavirus outbreak in TripAdvisor.

Several alternative destinations are available for decision-makers in destination decision-making (Decrop and Snelders, 2005). Due to the availability of rich information about travel products through different online sources, tourist decision-making has been enormously strengthened (Berne et al., 2012). It is more feasible for tourists to make their travel schedule independent of traditional travel agencies and tour operators based on numerous online sources of knowledge and travel services (Pan and Fesenmaier, 2006). Moreover, users' travel reviews are incredibly familiar with the travel information search process rather than commercial providers. Therefore tourists are now more and more aware of travel services and products, travel planning and transactions related to travel through electronic word-of-mouth (Tham et al., 2013).

A total of around 19 million tourists visited the Netherlands in 2018. The statistic report indicates a rise of approximately3 million visitors compared to 2017 (Statista, 2020a). Furthermore, inbound tourism is expected to continue to rise to 19 million and 21 million tourists in 2019 and 2020, respectively. The majority of people traveling in the Netherlands for holiday or business are from Germany, with about 5.24 million German visitors visiting their neighboring countries. They constitute more than half the total tourists visiting the Netherlands in 2017 along with the Belgians and the British (Statista, 2020a). The tourism sector is becoming increasingly important to the Netherlands economy year-on-year. Visitors spent a total of around € 78 billion (excluding outbound and other expenditures) in 2018. Tourists from abroad could spend a significant part of this expenditure, with inbound tourists spending about EUR 32.5 million (domestic expenditure worth EUR 45 billion). Relative to 2010, this is nearly double. One of the standout activities of tourists from abroad is visiting the Keukenhof in the Netherlands. Taken into account the flow of visitors to the Keukenhof, 20% of the visitors were domestic, 15% are German and 10% come from the USA, which are the top three (Statista, 2020a).

Travelers are increasingly relying on the web for other travelers' experiences and to find out what they can expect when they come to their destinations rather than on promotional ads or guides (Litvin et al., 2005). Social media platforms can be an excellent option to share data in real-time as they are an essential tool for public health and the development of the economy (Ahani et al., 2019b, 2017a; Giustini et al., 2018). The statistics show that the overall population in the Netherlands using social media was 61.23%. It is expected that this value will reach 65,76% by 2024. In comparison with the first year recorded, the increase would be around 4.5% (Statista, 2020c). The most popular internet sites for inbound and outbound tourists in the Netherlands are the online social networking site related to traveling. For example, TripAdvisor is a travel web site providing consumer reviews and other information on world destinations. This website offers travelers information, reviews and opinions on travel content and social travel forums (Ahani et al., 2019b; Nilashi et al., 2019a, 2018b, 2019b, 2019c). It has provided useful forums for new coronavirus disease outbreak for all countries involved, as well as for tourists from the Netherlands who are concerned about the outbreak. The platforms of TripAdvisor have provided information for Netherlands tourists in relatively real-time about the novel coronavirus. Tourists and hotel managers in TripAdvisor in the Netherlands can also provide useful information about the situation of a particular place for travel. This website has provided travelers with forums to reveal their concerns about the outbreak of coronavirus and share information about coronavirus travel. The following are just two examples of the concerns that the active contributors with different levels have of the coronavirus outbreak (see Fig. 1). With so many possibilities, travelers often need advice on where to go, see, visit and do. Tourists are generally helped by a travel officer, a person with knowledge and skills. However, human factors, such as lack of memory, a lack of knowledge about the world, countries and cities and their tourist options may restrict the recommendations from these agents, which may result in a low ability to match tourist requirements or wishes against the options stored within a database. The final decision sometimes depends far too much on a tour operator.

Recommender systems in several applications have already proven useful in coping with the problem of information overload (Bagherifard et al., 2017; Nilashi et al., 2017, 2015). Research on human decision-making in recommendation systems in this highly interdisciplinary area of research has become ever more important and popular. Häubl and Trifts (2000) examined user purchase decisions' quality and performance impact by recommendations agents. They have shown that the use of recommendations agents can reduce consumers' effort to search for product information, reduce their consideration size and enhance the quality of their purchase decisions. An online consumer review Deutsch and Gerard (1955) as a path to social influence can have two main roles –an informant and a recommender (Park et al., 2007). The online consumer reviews provide additional user-oriented information as an informant. They provide a negative/positive sign of popularity as a recommendation. As consumers simultaneously request product information and recommendations to purchase a product to learn about it and reduce uncertainty (Park et al., 2007; Rosen and Olshavsky, 1987), online consumer reviews that play both roles can meet the information needs of consumers completely. In addition, the travel agent may work with them to understand the customer's wishes, preferences, demands and, goals of the customer. Ricci and Werthner (2001) The challenge is posed by interacting with the customer via a dialog to identify the customer's interests. This dialog with the customer can be carried out using technological resources via textual messages. Once messaging is exchanged, the discussion session is scanned by an automated system to find subjects in the messages.

Big data analytics has been a key application area with tremendous potential and growth for hospitality and tourism. As (Filieri et al., 2015) state in their research; currently, travel reviews are an important source of information for travelers. Studies on the tourist industry have demonstrated a potential impact on hotel rooms' sales by customers (online consumer reviews or user ratings) (Ye et al., 2009). The previous research further investigated that online reviews influence travelers' decision-making on the selection of travel destinations (Arsal et al., 2008) and booking of hotels (Filieri and McLeay, 2014). Regarding travelers' decision-making, previous research also claims that online content generated by consumers would influence the entire stages of the travel preparation process (Kim et al., 2018). The content produced by the customer plays a major role in determining how tourist companies formulate their strategies and policies to better make business decisions and to provide the perfect supply of resources (Song and Liu, 2017).

Furthermore, social medic platforms have delivered significant support to countries, governments, health care agencies and businesses including tourism organizations. One of the most important functions of social media is the power to spread a broad range of information (Bakshy et al., 2012). Social media platforms share information in real-time for public health and business development

(Ahani et al., 2019b; Giustini et al., 2018). Emerging of social media and Web 2 has meaningfully impacted tourism information sources recently. Travelers continue to be mainly affected by the commentaries and thoughts of families and connections while organizing their travels (Hernández-Méndez et al., 2015). Not to mention that, this is the WOM that can simply spread through different social media channels. WOM is a discussion about a product or service that happen among individuals (Arndt, 1967). Indeed, the influence of WOM occurs in the last buying step since positive WOM communications support customers, decrease anxiety and doubt, and endorse guarantee (Abubakar et al., 2017; Assael, 1995; Chen et al., 2015). Electronic word of mouth (eWOM) or Electronic version of WOM is a continuing information sharing process between prospective, real, or previous customers about a product, service, or business, which is accessible to the public via the Internet (Ismagilova et al., 2019). The eWOM is also recognized as a significant source of information that considerably influences buying decisions (Kudeshia and Kumar, 2017; Lin et al., 2019). Specifically, WOM through social media (eWOM) can increase customer awareness, reduce risk regarding products or services and help travelers select their destinations (Abubakar and Ilkan, 2016; Grewal et al., 2003; Jalilvand and Samiei, 2012; Nilashi et al., 2018a).

It has been found that online reviewers can choose to write so that their experience is best represented (Wattanacharoensil et al., 2017). Opinions shared by peer travelers, thus assist in reducing the risk of a poor decision to tourists. But, due to the increasing number of opinions and reviews on products and services per experience, reading all reviews for an informed decision is difficult. Moreover, online travelers face complex decisions due to the wide variety of products, choices, and available information. Thus, online businesses are trying to support travelers' decision-making by providing advice from previous travelers and recommender systems. Accordingly, recommendation agents developed by machine learning techniques can be effective in the analysis of such social big data for the identification of useful patterns from the data and knowledge discovery. The recommendation agent is developed through the text mining approach. Many learning techniques for text mining have been developed to perform the data analysis on unstructured data (e.g., online reviews). One of these techniques is Latent Dirichlet Allocation (LDA), which is used for probabilistic topic modeling. This study uses LDA for online reviews analysis which, is provided in TripAdvisor forums of The Amsterdam Message Board regarding the COVID-19 outbreak. The data is crawled by a designed crawler from the TripAdvisor website.

Therefore, based on the explanation above, and since the tourism industry is considered one of the principal sectors influenced by the COVID-19 outbreak and due to COVID-19 outbreak developed into the main media occurrence and the worldwide catastrophe that enormously affected the tourism sector and the tourists' travel behavior globally (Neuburger and Egger, 2020). Therefore, this situation recommendation system, which is considered an intelligent system and supporting tool in the decision-making process in online retailing websites, can be effective (Abumalloh et al., 2020). Besides this recommender system should be flexible and inform the instance of outbreaks and consider the users' requirements. Nilashi et al. (2018b) stated that recommendation agents are essential tools for travel agencies to aid customers in their decision-making procedures.

Recently, numerous studies conducted on tourism recommendation systems (Jeong et al., 2020a; Yochum et al., 2020) and have discussed research challenges and a general overview of this system. For instance, Bahramian and Abbaspour (2015) conducted research on the tourism recommender system and developed a new recommender system to overcome information overload difficulty. Figueredo et al. (2018) developed a tourism recommender system for smart tourism destinations based on emerging methods using deep learning and fuzzy logic techniques. Loh et al. (2003) presented a tourism recommender system for travel agents by utilizing a text mining approach. Santos et al. (2016) proposed a tourism recommendation system to assess user profile formation concerning new information associated with the user's physical and psychological functionality stages. Jeong et al. (2020b) in their study developed recommendation systems for tourism based on the information in tourist sites via big data social network investigation. While these studies suggest fascinating investigations into various perspectives of recommendation systems, the novelty of our research varies from the previous studies; that is, we focus on the recommendation agents by using machine learning and text mining methods. Best of our knowledge, no research has been conducted to examine the tourism industry's recommendation system, especially in this circumstance of the COVID-19 outbreak. Therefore, the contribution of this study is summarized as follows:

- This study develops a recommender system based on text mining and prediction machine learning techniques.
- This study used big data analytic tools to perform analysis on of big social data

to help the customers and businesses for better decision making in an unexpected event like the Coronavirus outbreak.

## 2. Literature review

### *2.1. Coronavirus and its impact on the Netherlands tourism*

Coronavirus is an infectious agent, hugely impacted individuals' social life all around the world. This virus, also known as Covid-19, creates respiratory illness with symptoms such as a cough, fever, along with breathing difficulties in more severe cases. As for today, there is no vaccine to prevent Covid-19 prevalence or any medication to treat Covid-19 patients. The only known measures, recommended by the world health organization (WHO) are the regular washing of hands, avoid touching the face, attending to the social distancing rules and home isolation. Among all the suggested measures, maintain a social isolation for a long period is difficult, considering that people would like to keep their social life and perform on their job duties. For instance, today people would like to socialize, meet, and greet others to advance a sense of their social life (Kizgin et al., 2019). However, due to the Coronavirus outbreak, it is impossible to maintain a healthy social life, given the rapid community transmission of this virus, which creates the profound fear in the hearts and minds of the people.

The new COVID-19 virus took hold of other regions after months of rapid spread within China. By 19 March 2020, the Dutch authorities reported a total of 2460 cases of coronavirus. On 27 February 2020, the coronavirus officially entered the Netherlands when a Dutch resident returned from Italy's Lombardy region. A Dutch resident traveled to northern Italy was also the second identified case in this country (Statista, 2020b). The number of patients was adjusted downwards on 3 March. Number of new daily Coronavirus (COVID-19) cases in the Netherlands as of April 14, 2020 is presented in Fig. 2 (Statista, 2020b).

As the coronavirus disease spreads worldwide, the travel industry is being drastically frozen when travel bans are introduced. Global travelers are increasingly concerned about the outbreak. Almost half (42 percent) of travelers worldwide who have booked trips over the next 6–12 weeks have already canceled their travel plans or plan to cancel because of coronavirus concerns, the study finds. The entry conditions in the Netherlands will be stricter from Thursday, 19 March 2020, at 18:00. In 2020, the Netherlands is expected to be visited by around 1,53 million tourists from Asia. Most people from China (incl. Hong Kong) are expected to come with 305,000 visitants, while 195,000 and 130,000 from India and Japan are expected to come. Compared to the previous year's volume of tourists in China, however, the statistical report decreased by 20% (Statista, 2020). This is mainly due to the outbreak of coronavirus.

### 2.2. eWOM and Travellers' information sharing for coronavirus outbreak

The importance of word-of-mouth (WOM) in shaping consumer opinions and behaviors have been long understood by researchers. (Arndt, 1967; Day, 1971; King et al., 2014). The study of WOM communication also included the research of eWOM with the advent of the Internet. eWOM is any positive or negative statement of a product or company made available on the Internet by potential customers to the groups of users who seek specific information in the online environment (Hennig-Thurau et al., 2004). eWOM has various unique features, including greater scalability, accessibility, measurability, and quantifiability, that distinguish it from WOM (Cheung and Thadani, 2012; Hung and Li, 2007). As social media platforms are increasingly used, eWOM becomes a popular source of reliable data and influences consumers (Gauri et al., 2008). It is an important source of information for travelers looking for information about their destination and facilitates their decision-making with respect to on-line acquisitions of tourism products or services (Lu et al., 2010). In prior studies, its impact on the behavioral patterns and travel intentions has been identified (Di Pietro et al., 2012) and

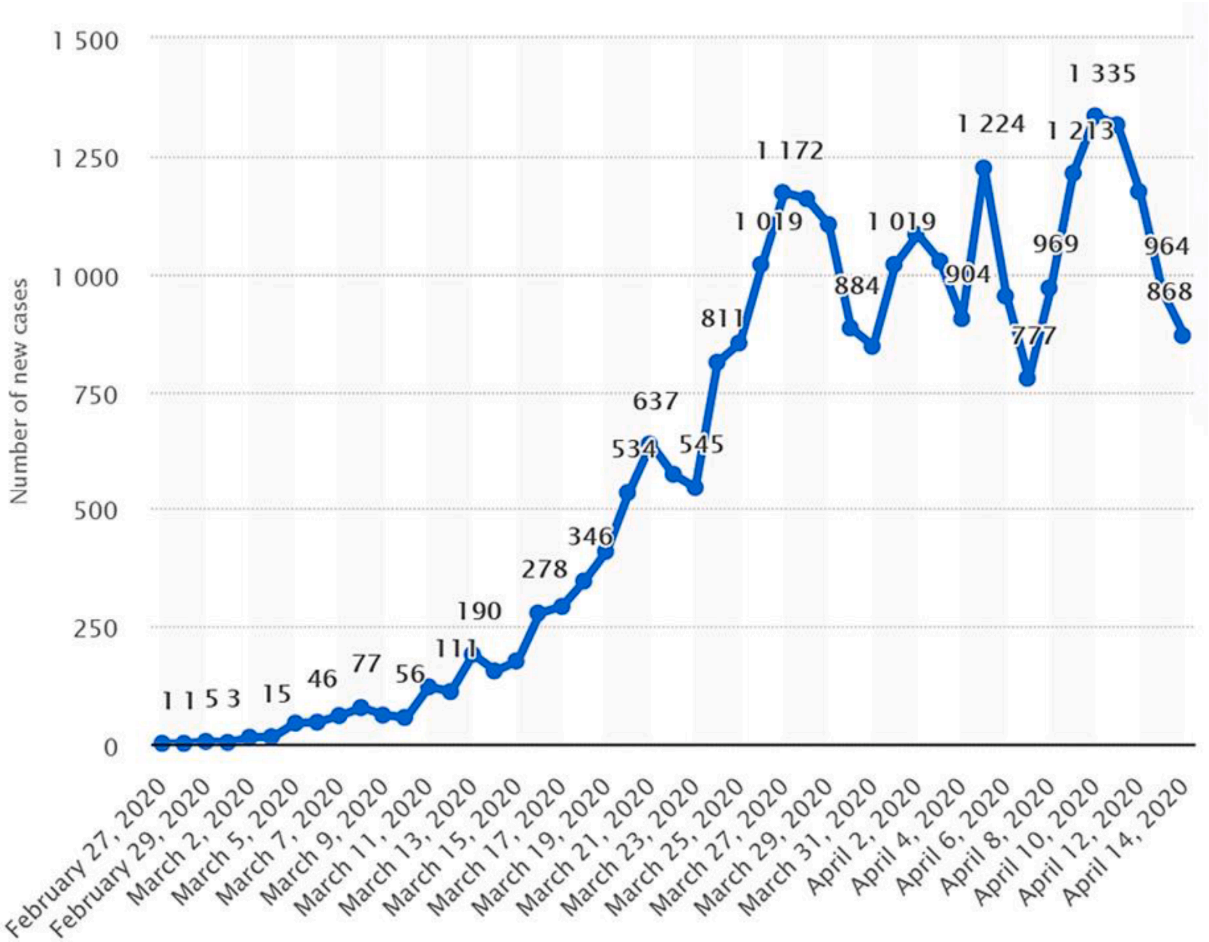


**Fig. 2.** Number of new daily Coronavirus (COVID-19) cases in the Netherlands as of April 14, 2020 (Statista, 2020b).

purchase intentions (Sparks and Browning, 2011). Consumer behavior research suggests that eWOM and product assessments have an emotional and cognitive attitude towards the consumer (Harrison-Walker, 2001).

The communication today is significantly different as social media platforms have a key role in the distribution of information

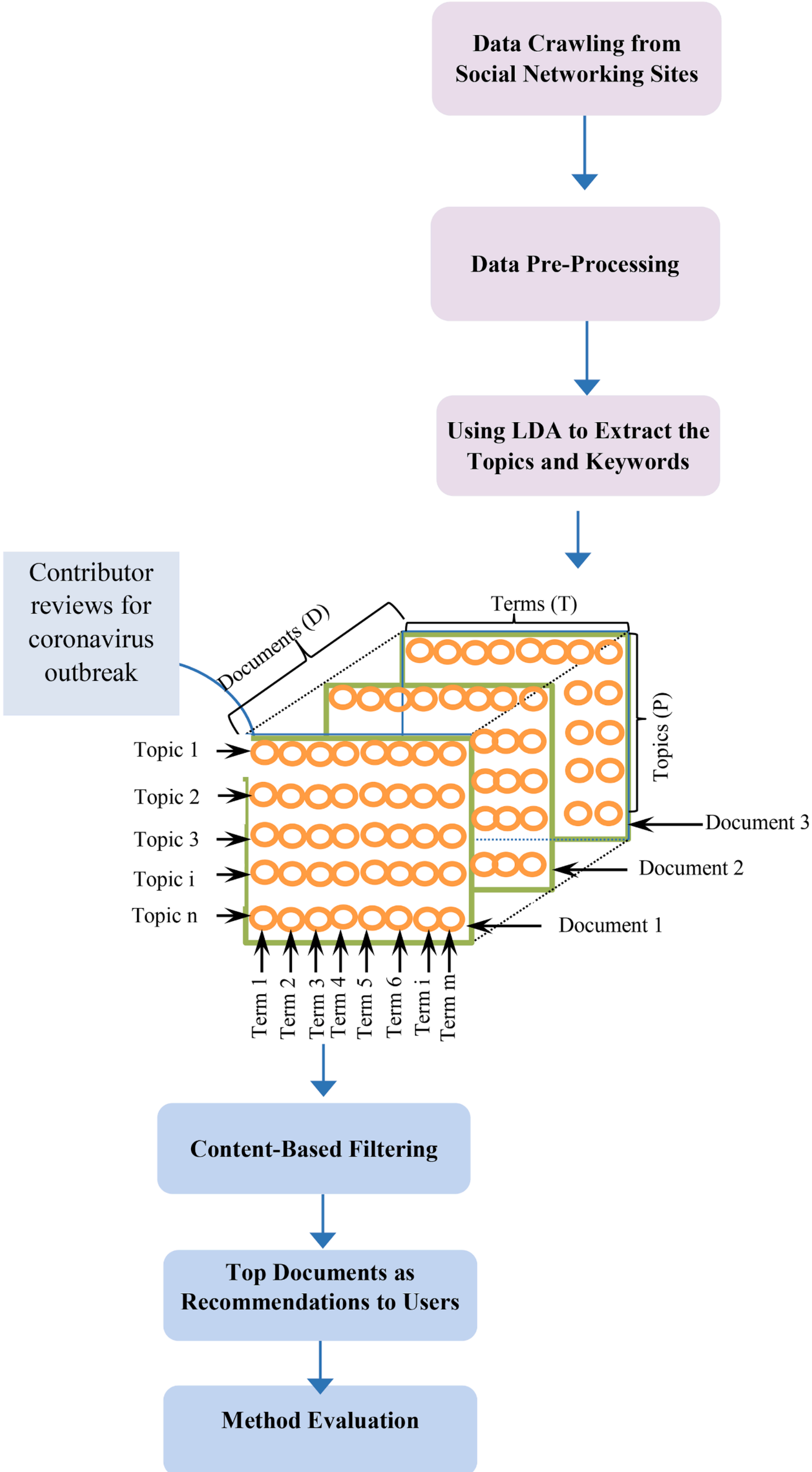


**Fig. 3.** Data anlytic procedure.

which allows people to concurrently share information with numbers of individuals (Bakshy et al., 2012). Social media have provided an online environment for people to be together, work together and share knowledge. In fact, these platforms have developed as a practical tool, emerging and maintaining social relationships (Ellison and Boyd; Kane et al., 2014). In addition to help with the maintenance of the healthy social life, the online platforms and chancels, is helping businesses to continue running remotely in which customers can even evaluate their performance, using social media (Etter et al., 2019). For instance, TripAdvisor was founded 20 years ago but it wasn't a user generated social media site. Now, this social network provides customers with two-way communications to receive information from tourism organizations and creating content regarding their travels' experiences. TripAdvisor is a travel social media that help travelers to get travel information, post reviews and opinions about travel content and engage in social travel forums (Ahani et al., 2019a). When the perceived risk of traveling increases, travelers are more willing to rely on social media and user generating content (UGC) in decision making (Amatulli et al., 2019; Ukpabi and Karjaluoto, 2018).

Recently, social media has also been effective in Coronavirus outbreak, specially in spreading the coronavirus through the travellers. The fact is that without social media contributions, it was difficult to improve the travelers' awareness for Coronavirus outbreak. Let's take you back a little bit, assuming that the Coronavirus outbreak had occurred 20 years ago. What do you think would have happened? Was it possible to keep people at home isolation asking them to fulfil their job duties online and from home and attend to their social activities online? Was it possible to inform and update people on the outbreak of this virus as quick as today? What about travel decisions, was it possible for people to make travel decisions without having accurate information regarding the outbreak situation in different destinations, or flight cancelation, and travel bans? It would be defiantly hard as at that time there were no social media including Facebook, Twitter, and other social network platforms.

Therefore, travelers need more external knowledge to assist them in perform purchase decisions throughout the evaluation stage. In this regard, travelers depend more profoundly on eWOM to decrease perceived risk and doubt, which then impacts their decisions and intention on the booking (Tsao et al., 2015). The eWOM on TripAdvisor, becomes significant when the travelers have narrowed information regarding a travel destination to increase their awareness (Shome, 2020). In the case of the Coronavirus outbreak quantity of travel eWOM posted on social media platforms (TripAdvisor forums) provided real-time information on the COVID-19 and can be effective in the brief description and forecasting of various COVID-19 travel news tips and statistics. Besides, that can increase travelers' awareness about coronavirus prevention.

### *2.3. Information sharing theory*

The information sharing theory derived from social exchange theory was proposed by Constant et al. (1994) to investigate the effects on individuals' intentions to share information. It is based on the idea that "organizational culture and policies, as well as personal factors, can influence peoples' attitudes about information sharing" (Constant et al., 1994). The theory of information sharing states that people are determined by individual factors, for example, power and reciprocity, and by the social and organizational factors of information sharing. The information sharing theory proceeds beyond communications and information transfers between friends and individual communications to incorporate "organizationally remote strangers they will never meet in person"(Zaheer and Trkman, 2017). Furthermore, information sharing theory also expresses that individuals sharing information are influenced by the considerations of rational self-interest, organizational, and social setting (Qi, 2015).

Nowadays, the information sharing in the tourism industry is considered as a critical domain, and tourists are frequently longing for information about their situation (Mupfiga, 2015). The information of tourists' requirements comprises of united information of the destination as well as real-time support through travel investment; real time support through travel investment; and distribution experiences with different travelers simply Tourists require the support of the information's accessibility post-visit for peer evaluation. In this research, the association of tourism information requirements is essential to discover the information to be distributed and performed. In our case when people discovered that that sharing information in social media is usual, precise, and socially wanted workspace behavior they have more feelings to continue to share information. For instance, in the case of COVID-19, TripAdvisor as a platform for information sharing is essential in a collaborative network for sharing information. Furthermore, it is accessible to provide evaluations and judgments regarding any tourism experience by further functionality that usually is not accessible on websites. Mahakata et al. (2017) stated that online information sharing could aid decrease the time needed for information sharing and publicly the system is available by anyone from anyplace over the world. Therefore, all tourism stakeholders as well as travelers can acquire unified comprehensive information about destinations.

## 3. Method and data analysis

The proposed method, which combines textual modeling approach with the content-based filtering is presented in Fig. 3. The main steps of the proposed method are: data crawling from social networking site, data pre-processing, topic and keyword extraction from the textual data, content-based filtering and providing recommendations to the users. Each step of the proposed method is introduced in the following sections.

**Data Collection and Pre-Processing:** The data is crawled by a designed crawler from TripAdvisor website. The collected data stored in the datasets. In Fig. 2, a part of users' number of reviews and posts is presented. Each user has provided his/her comment on the question provided for coronavirus outbreak in TripAdvisor' message board. The preprocessing of text used steps which were similar to previous research (Lee and Bradlow, 2006), including word stemming; word tokenization; removing non-English characters and words; replaced common negative words; POS tagging; and deletion of words in low frequency (down from 2 percent). This study uses recent developments in the field of machine and natural language learning in the field of the technology and techniques used to effectively extract the main topics and important terms from a wide range of text data. A topic model is a type of probability model for the discovery of the topics found in a document collection. We applied LDA on the collected data and stored the weights of the terms in each topic of the documents in a 3-dimensional tensor (see Fig. 4). The tensor of data mainly included documents, topics and the terms.

**Topic Modeling:** Topic analysis has been recently the center of attention in the area of machine learning as well as text mining (Henderson and Eliassi-Rad, 2009; Lukins et al., 2008). It is by definition a process through which the latent information is discovered in a collection. One of the instances of probabilistic topic modeling strategies (Redner and Walker, 1984) is LDA (Blei et al., 2003), according to which a number of topics will be covered by a document and sampling of every word in the document **is** performed considering the probability distributions with various parameters; therefore, every word is produced with a hidden variable which shows its original distribution. When the scope of representing every topic in the document is computed, it is possible to represent the document at a higher level compared to the potential level, through BOW technique which reflects a series of topics. The graphical description of the LDA approach is presented in Fig. 5. The LDA generative procedure is defined as follows:

**Algorithm 1.** LDA Procedure

1. For each topic $z \in Z$
   - A multinomial distribution is draw as $\varnothing_z$ $Dir(\overrightarrow{\beta})$.
2. For every user $u \in U$,
   - A multinomial distribution$\theta_u$ $Dir(\overrightarrow{\alpha})$ is drawn.
   - For every word $w \in D_u$,

(a) A topic $z$ $Multinomial(\overrightarrow{\theta_u})$ is drawn.(b) A word $w$ $Multinomial(\overrightarrow{\varnothing_z})$ is drawn

In LDA, multi-nominal distributions of $\overrightarrow{\theta_u}$ are assumed and $\overrightarrow{\varnothing_z}$ are depicted from Dirichlet distribution through two parameters $\overrightarrow{\alpha}$ and $\overrightarrow{\beta}$. Every word $w$ in $D_u$ is considered as chosen by the initially depicting a topic $z$ following $\overrightarrow{\theta_u}$ and then selecting a word $w$ in the text corpus from the associated distribution $\overrightarrow{\varnothing_z}$ of the chosen topic z. Based on the LDA scheme, the possibility of a word $w$ originated by user $u$ is predicted as:

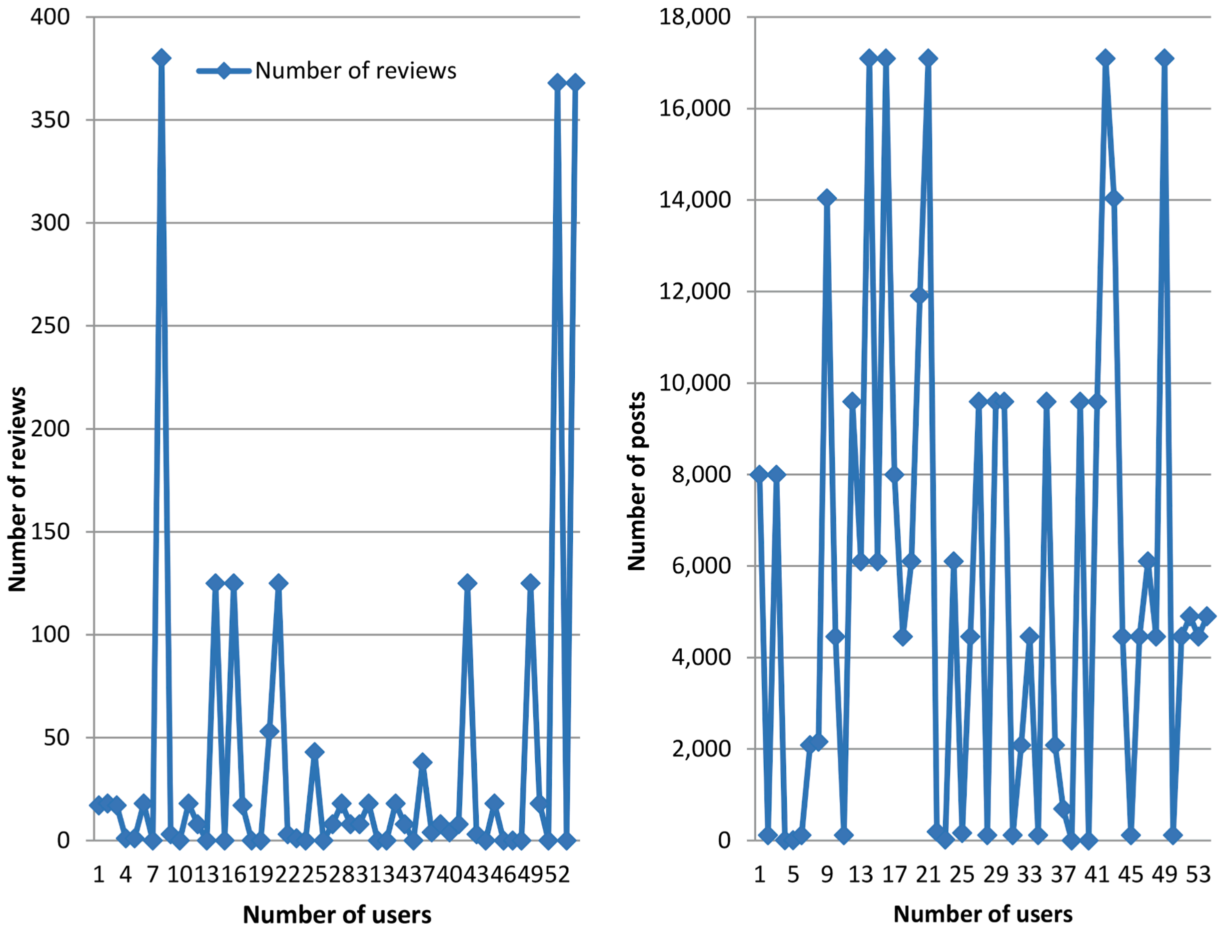


**Fig. 4.** Data anlytic procedure.

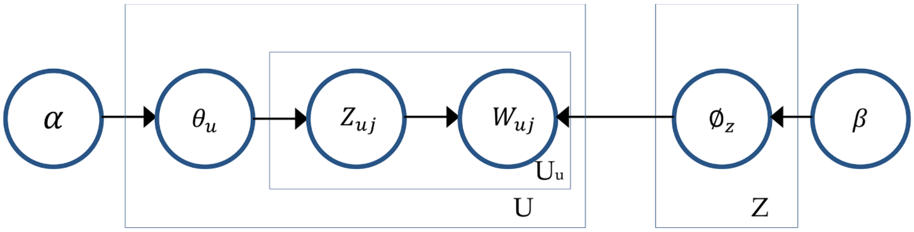


**Fig. 5.** The graphical representation of LDA.

$$\int Dir(\theta_u; u)\left(\sum_{z=1}^{|Z|}\theta_{uz}\varnothing_{zw}\right)d\theta_u \tag{1}$$

We use the LDA technique to extract the principal dimensions and label them in all collected reviews by users (contributor). The LDA identified 10 subjects and showed the top 20 words and their relative weight in each topic. Dimensions were labeled based onthe identification of a logic link between the most common words for a subject. The results of LDA for two topics are presented in Fig. 6.

**Content-Based Filtering:** To help users retrieve the relevant resources, recommendation

systems have been developed as decision support systems (Nilashi et al., 2018a). Two basic approaches used in recommendation systems include collaborative and content-based filtering. The former employs feedback from users with similar interests, the latter is based on the functionality of each user's chosen resources. Recommender systems can use a list of recommendations to assess user behavior more accurately. In this work, as the online reviews are involved as resources, item vectors are defined by the users' online reviews, i.e., text that describes the situation caused by COVID-19 outbreak (see Fig. 1). In order to build item vectors (features from documents), a text mining approach, the LDA algorithm, can be used to extract topic information from the text as a word probability. Since each document is distributed according to its own topic, the cosine-based similarity measure between two documents can be applied by viewing each as a (theme-based) vector.

**Top Documents as Recommendations to Users:** Finally, in this step, the Top-N recommendation is established for the active user (Nilashi et al., 2019c). This can be done by calculating the similarity between the documents to be recommended to the active user. Therefore, we can simply select the similarities in the order below and choose the first N documents for creating the list of recommendations.

**Method Evaluation.** The F-measure metric is used to evaluate the quality of recommendations (Nilashi et al., 2018a). F-measure indicates a single value obtained combining both the precise and the recall. This measure is considered in the recommendation agents' context for the overall usefulness of the recommendation list. A weighted harmonic means of two metrics recall and precision forms F1 as:

$$F = \frac{1}{\frac{\beta^2}{1+\beta^2}\times\frac{1}{Precision}+\frac{1}{1+\beta^2}\times\frac{1}{Recall}} = \frac{(1+\beta^2)Recall.Precision}{\beta^2.Recall+Precision} \tag{2}$$


**Fig. 6.** LDA results for two topics.

In the above equation, the weighting factor β indicates the corresponding significant of precision against the recall. In the case of β = 1, the relative F-measure score is associated with the F1 score. This study concentrates on the use of the F1 scores for the evaluation of the accuracy in a prediction model. The results for precision, recall and F1-measure results for recommendations based on number of topics (5, 10, 15 and 20) are provided in Fig. 7.

## 4. Discussion

The current Coronavirus outbreak has had a huge impact on different industries including tourism. The tourism industry is currently one of the most disturbing segments. In the current Coronavirus outbreak, travelers and tourism organizations can provide useful information regarding the condition of different destinations (Ahani and Nilashi, 2020). Today, different types of social media have enlarged the number of individuals using the Internet to access information about their future travel destinations (Leung et al., 2013; Litvin et al., 2008; Xiang and Gretzel, 2010). Bringing an example, social media channels make it possible to increase individuals' awareness on the symptoms of this virus as well as the preventive approaches. On social media platforms such as Twitter, Facebook, and TripAdvisor, clinicians, medical specialists, tourism organizations, governments and individuals are regularly updating people regarding the prevalence of the outbreak.

It has always been essential for travel agencies to improve the quality of online services on social networking sites. Moreover, it is an important task for the tourism website's search engine to help users make good decisions on tourism platforms. Therefore, it has been in the interest of many researchers to develop more reliable and useful search engines to help travel services providers improve their systems (Fesenmaier et al., 2010). The importance of recommending systems for e-commerce consumer choices has already been analyzed in previous studies. In tourism, travelers are also overwhelmed by the fact that they must compare too many suggestions, the only difference being that they have small details and especially in unexpected events, the most relevant recommendations for the decision-making process should be received. Sophisticated recommendation agencies are therefore needed before taking a decision to solve overloads of information and make appropriate recommendations. Different types of possible online recommendation sources (e.g. experts, clients) are available. For this study, we concentrated on advice that previous customers published online in the form of online review.

Many previous studies have analyzed the impact on travellers' behavior from online reviews, and several studies examine the impact and use of recommendation systems. This research expands knowledge about online recommendations and their impact on decision-making by travelers. In practical terms, potential customers are often seeking several suggestions to facilitate their decision-making and make the right choice from a large selection of online alternatives. During natural disasters, unexpected events or emergency situations, an essential requirement for an effective and right decision making and emergency management is information sharing (Carminati et al., 2013). According to WHO, reachable knowledge is an important primary phase in the conversion of knowledge from scholars to managers, policymakers and other stakeholders (Dye et al., 2013). As social media platforms have become a vital part of today's people life (Ahani et al., 2017b), a reliable collaborative platform for information sharing may be beneficial for managing the impact of unexpected events like Coronavirus outbreak on the global economy. Social networking sites provide forums to collect a considerable amount of data which are useful for awareness of customers and businesses on the current situation for their right decision making at the right time. Accordingly, it is suggested the use of big data analytic tools to perform analysis on this type of big social data to help the customers and businesses for better decision making in an unexpected event like Coronavirus outbreak. In addition, according to the previous studies, increasing the volume of online reviews will better help mitigate negative comments (Teixeira and Kornfeld, 2013), improve consumer perception (Tsao et al., 2015), and eventually, improve operational performance (Kim et al., 2015). Thus, the service provider must consider effective feedback systems with sophisticated knowledge sharing channels during natural disasters, unexpected events or emergency situations. This will accordingly improve the traveller's awareness for right

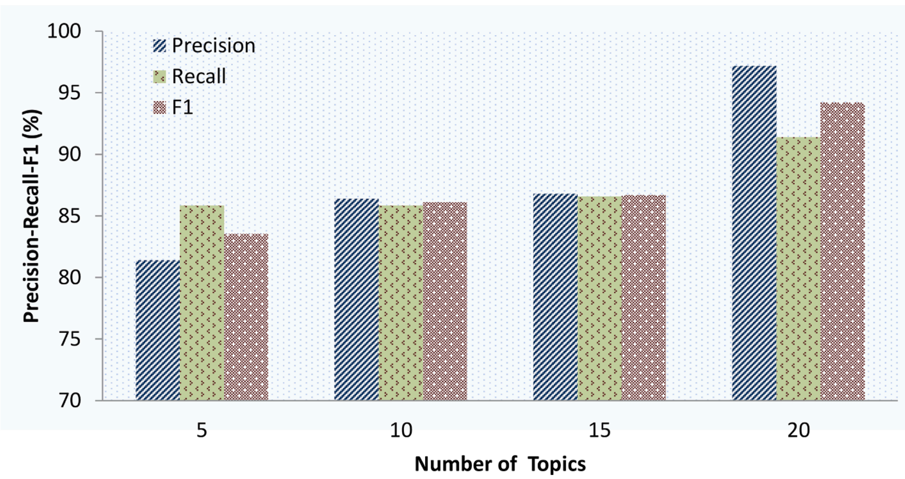


**Fig. 7.** The precision, recall and F1-measure results for recommendations based on number of topics.

decision making through eWOM.

Therefore, prior studies agree that online recommendations have become necessary when doing bookings and influence on revenues as well as contribute to information sharing and impact travelers' decision-making. For example, the finding of this study is consistence with Brazytė et al. (2017) who declared that eWOM and online societies perform a significant role in the travelers' decision-making manner. Similarly, Law et al. (2010) and Kotoua (2017) stated that social media and positive WOM are significant to the hospitality and the tourism business as well as websites service providers on the internet. Websites support to develop destinations and impact tourists' decision-making processes for choosing the destinations of their passion. Moreover, this is similar to the findings of Zeng and Gerritsen (2014) they agreed that information sharing on social media websites is an essential basis of evidence that can aid tourists in travel decision-making. Nezakati et al. (2015) and Jacobsen and Munar (2012) correspondingly stated that social media could similarly be utilized during the travel preparation process and also after travel for sharing knowledge. An improved method of social media makes eWOM closer to conventional WOM communication which is, however, a significant information source for travel preparation and decision-making.

## 5. Theoretical and practical implications

This study adopted a framework for the recommendation agents and uncovered how social networking websites and online reviews could be effective in unexpected events for travelers' decision making. Thus, the theoretical contribution of this study is through the lens of information sharing theory. In this research, the identification of travel information requirements is vital to discover the information to be distributed and presented. Based on this theory, the principal outcome of this research reveals that social media has an essential role as a source of information to assist the tourist in each step of travel decision-making, and at every stage, the tourist is utilizing information in taking whole activities initiated. Significantly, based on the information sharing theory, people may actively share information eWOM through social media which is also identified as an essential source of information that can aid tourists in decision making.

This study also presents some extremely effective practical implications as follows: this study empirically showed that practitioners need to attempt to encourage tourists for social networks to engage in eWOM for the outbreak of COVID-19 and tend to decrease the possibility of poor decisions. Therefore, the travel industry needs to take steps to comprehend how to engage these travelers. The authors likewise recommend that advertising practitioners engage their traveler bases directly through social media platforms. Moreover, practitioners should be cautious about what travelers share on social media because, in unpredictable and unique occasions of the COVID-19 outbreak, tourists need real information to satisfy their doubts and concern.

## 6. Conclusion

This study presents that social media is considered an essential tool and platform for sharing data in real-time. Additionally, the eWOM is also identified as a critical source of information that considerably impacts on tourists travel decision making as well as increase traveler awareness regarding their destination selection. This study applied big data analytic tools to analyze social big data to aid the travelers and industries to improve decision making in an unpredicted occasion like the Coronavirus outbreak. Moreover, we used Latent Dirichlet Allocation for online reviews analysis which is provided in TripAdvisor forums of The Amsterdam Message Board regarding the COVID-19 outbreak. Accordingly, the recommendation agent developed based on text mining and prediction machine learning techniques. The results of this study revealed that how social networking websites and online reviews can be useful in unexpected events for travelers' decision making. Although the proposed method has achieved good results from the social media data, the method can be further developed through sentiment models and other machine learning techniques. As the method was developed through non-incremental machine learning techniques, the use of incremental machine learning techniques may have better performance on the social big datasets during the COVID-19 outbreak.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## References

Abubakar, A.M., Ilkan, M., 2016. Impact of online WOM on destination trust and intention to travel: A medical tourism perspective. J. Destinat. Market. Manage. 5 (3), 192–201.
Abubakar, A.M., Ilkan, M., Al-Tal, R.M., Eluwole, K.K., 2017. eWOM, revisit intention, destination trust and gender. J. Hospital. Tour. Manage. 31, 220–227.
Abumalloh, R., Ibrahim, O., Nilashi, M., 2020. Loyalty of young female Arabic customers towards recommendation agents: A new model for B2C E-commerce. Technol. Soc. 101253.
Ahani, A., Nilashi, M., 2020. Coronavirus Outbreak and its Impacts on Global Economy: The Role of Social Network Sites. J. Soft Comput. Decis. Supp. Syst. 7 (2), 19–22.
Ahani, A., Nilashi, M., Ibrahim, O., Sanzogni, L., Weaven, S., 2019a. Market segmentation and travel choice prediction in Spa hotels through TripAdvisor's online reviews. Int. J. Hospit. Manage. 80, 52–77.
Ahani, A., Nilashi, M., Yadegaridehkordi, E., Sanzogni, L., Tarik, A.R., Knox, K., Samad, S., Ibrahim, O., 2019b. Revealing customers' satisfaction and preferences through online review analysis: The case of Canary Islands hotels. J. Retail. Consum. Serv. 51, 331–343.
Ahani, A., Rahim, N.Z.A., Nilashi, M., 2017a. Firm performance through social customer relationship management: Evidence from small and medium enterprises. In: 2017 International Conference on Research and Innovation in Information Systems (ICRIIS). IEEE, pp. 1–6.

Ahani, A., Rahim, N.Z.A., Nilashi, M., 2017b. Forecasting social CRM adoption in SMEs: A combined SEM-neural network method. Comput. Hum. Behav. 75, 560–578.
Amatulli, C., De Angelis, M., Stoppani, A., 2019. Analyzing online reviews in hospitality: data-driven opportunities for predicting the sharing of negative emotional content. Curr. Issu. Tour. 22 (15), 1904–1917.
Arndt, J., 1967. Role of product-related conversations in the diffusion of a new product. J. Mark. Res. 4 (3), 291–295.
Arsal, I., Backman, S., Baldwin, E., 2008. Influence of an online travel community on travel decisions, Information and communication technologies in tourism 2008. Springer 82–93.
Assael, H., 1995. Consumer behavior and marketing action.
Bagherifard, K., Rahmani, M., Nilashi, M., Rafe, V., 2017. Performance improvement for recommender systems using ontology. Telematics Inform. 34 (8), 1772–1792.
Bahramian, Z., Abbaspour, R.A., 2015. AN ONTOLOGY-BASED TOURISM RECOMMENDER SYSTEM BASED ON SPREADING ACTIVATION MODEL. International Archives of the Photogrammetry. Rem. Sens. Spatial Inf. Sci. 40.
Bakshy, E., Rosenn, I., Marlow, C., Adamic, L., 2012. The role of social networks in information diffusion. In: Proceedings of the 21st international conference on World Wide Web, pp. 519–528.
Berne, C., Garcia-Gonzalez, M., Mugica, J., 2012. How ICT shifts the power balance of tourism distribution channels. Tour. Manage. 33 (1), 205–214.
Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. J. Mach. Learn. Res. 3 (Jan), 993–1022.
Brazytė, K., Weber, F., Schaffner, D., 2017. Sustainability management of hotels: how do customers respond in online reviews? J. Qual. Assuran. Hospit. Tour. 18 (3), 282–307.
Carminati, B., Ferrari, E., Guglielmi, M., 2013. A system for timely and controlled information sharing in emergency situations. IEEE Trans. Dependable Secure Comput. 10 (3), 129–142.
Chen, C.-H., Nguyen, B., Klaus, P.P., Wu, M.-S., 2015. Exploring electronic word-of-mouth (eWOM) in the consumer purchase decision-making process: the case of online holidays–evidence from United Kingdom (UK) consumers. J. Travel Tour. Market. 32 (8), 953–970.
Cheung, C.M., Thadani, D.R., 2012. The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decis. Support Syst. 54 (1), 461–470.
Constant, D., Kiesler, S., Sproull, L., 1994. What's mine is ours, or is it? A study of attitudes about information sharing. Informat. Syst. Res. 5 (4), 400–421.
Day, G.S., 1971. Attitude change, media and word of mouth. J. Advert. Res.
Decrop, A., Snelders, D., 2005. A grounded typology of vacation decision-making. Tour. Manage. 26 (2), 121–132.
Deutsch, M., Gerard, H.B., 1955. A study of normative and informational social influences upon individual judgment. J. Abnorm. Soc. Psychol. 51 (3), 629.
Di Pietro, L., Di Virgilio, F., Pantano, E., 2012. Social network for the choice of tourist destination: Attitude and behavioural intention. J. Hospital. Tour. Technol.
Dye, C., Reeder, J.C., Terry, R.F., 2013. Research for universal health coverage. American Association for the Advancement of Science.
Ellison, N.B., Boyd, D., Sociality through social network sites.
Etter, M., Ravasi, D., Colleoni, E., 2019. Social media and the formation of organizational reputation. Acad. Manag. Rev. 44 (1), 28–52.
Fesenmaier, D., Xiang, Z., Pan, B., Law, R., 2010. An analysis of search engine use for travel planning. na.
Figueredo, M., Ribeiro, J., Cacho, N., Thome, A., Cacho, A., Lopes, F., Araujo, V., 2018. From photos to travel itinerary: A tourism recommender system for smart tourism destination. In: 2018 IEEE Fourth International Conference on Big Data Computing Service and Applications (BigDataService). IEEE, pp. 85–92.
Filieri, R., Alguezaui, S., McLeay, F., 2015. Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. Tour. Manage. 51, 174–185.
Filieri, R., McLeay, F., 2014. E-WOM and accommodation: An analysis of the factors that influence travelers' adoption of information from online reviews. J. Travel Res. 53 (1), 44–57.
Gauri, D.K., Bhatnagar, A., Rao, R., 2008. Role of word of mouth in online store loyalty. Commun. ACM 51 (3), 89–91.
Giustini, D., Ali, S.M., Fraser, M., Boulos, M.N.K., 2018. Effective uses of social media in public health and medicine: a systematic review of systematic reviews. Online J. Public Health Informat. 10 (2).
Grewal, R., Cline, T.W., Davies, A., 2003. Early-entrant advantage, word-of-mouth communication, brand similarity, and the consumer decision-making process. J. Consum. Psychol. 13 (3), 187–197.
Harrison-Walker, L.J., 2001. The measurement of word-of-mouth communication and an investigation of service quality and customer commitment as potential antecedents. J. Serv. Res. 4 (1), 60–75.
Häubl, G., Trifts, V., 2000. Consumer decision making in online shopping environments: The effects of interactive decision aids. Market. Sci. 19 (1), 4–21.
Henderson, K., Eliassi-Rad, T., 2009. Applying latent dirichlet allocation to group discovery in large graphs. In: Proceedings of the 2009 ACM symposium on Applied Computing, pp. 1456–1461.
Hennig-Thurau, T., Gwinner, K.P., Walsh, G., Gremler, D.D., 2004. Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? J. Interact. Market. 18 (1), 38–52.
Hernández-Méndez, J., Muñoz-Leiva, F., Sánchez-Fernández, J., 2015. The influence of e-word-of-mouth on travel decision-making: consumer profiles. Curr. Issues Tour. 18 (11), 1001–1021.
Hung, K.H., Li, S.Y., 2007. The influence of eWOM on virtual consumer communities: Social capital, consumer learning, and behavioral outcomes. J. Advert. Res. 47 (4), 485–495.
Ismagilova, E., Slade, E.L., Rana, N.P., Dwivedi, Y.K., 2019. The effect of electronic word of mouth communications on intention to buy: A meta-analysis. Informat. Syst. Front. 1–24.
Jacobsen, J.K.S., Munar, A.M., 2012. Tourist information search and destination choice in a digital age. Tour. Manage. Perspect. 1, 39–47.
Jalilvand, M.R., Samiei, N., 2012. The impact of electronic word of mouth on a tourism destination choice. Intern. Res.
Jeong, C.-S., Lee, J.-Y., Jung, K.-D., 2020a. Adaptive Recommendation System for Tourism by Personality Type Using Deep Learning. Int. J. Internet, Broadcast. Commun. 12 (1), 55–60.
Jeong, C.-S., Ryu, K.-H., Lee, J.-Y., Jung, K.-D., 2020b. Deep Learning-based Tourism Recommendation System using Social Network Analysis. Int. J. Intern., Broadcast. Commun. 12 (2), 113–119.
Kane, G.C., Alavi, M., Labianca, G., Borgatti, S.P., 2014. What's different about social media networks? A framework and research agenda. MIS quarterly 38 (1), 275–304.
Kim, C.S., Bai, B.H., Kim, P.B., Chon, K., 2018. Review of reviews: A systematic analysis of review papers in the hospitality and tourism literature. Int. J. Hospital. Manage. 70, 49–58.
Kim, W.G., Lim, H., Brymer, R.A., 2015. The effectiveness of managing social media on hotel performance. Int. J. Hospital. Manage. 44, 165–171.
King, R.A., Racherla, P., Bush, V.D., 2014. What we know and don't know about online word-of-mouth: A review and synthesis of the literature. J. Interact. Market. 28 (3), 167–183.
Kizgin, H., Jamal, A., Rana, N., Dwivedi, Y., Weerakkody, V., 2019. The impact of social networking sites on socialization and political engagement: Role of acculturation. Technol. Forecast. Soc. Chang. 145, 503–512.
Kotoua, S., 2017. Information Technology and Destination Marketing: Present and Future Challenges of the Prospects of the Tourism Industry in Ghana.
Kudeshia, C., Kumar, A., 2017. Social eWOM: does it affect the brand attitude and purchase intention of brands? Manage. Res. Rev.
Law, R., Qi, S., Buhalis, D., 2010. Progress in tourism management: A review of website evaluation in tourism research. Tour. Manage. 31 (3), 297–313.
Lee, T.Y., Bradlow, E.T., 2006. Automatic construction of conjoint attributes and levels from online customer reviews. University of Pennsylvania. The Wharton School Working Paper OPIM WP 06-08-01.
Leung, D., Law, R., Van Hoof, H., Buhalis, D., 2013. Social media in tourism and hospitality: A literature review. J. Trav. Tour. Market. 30 (1–2), 3–22.
Lin, X., Featherman, M., Brooks, S.L., Hajli, N., 2019. Exploring gender differences in online consumer purchase decision making: An online product presentation perspective. Informat. Syst. Front. 21 (5), 1187–1201.

Litvin, S.W., Blose, J.E., Laird, S.T., 2005. Tourists' use of restaurant webpages: Is the internet a critical marketing tool? J. Vacat. Market. 11 (2), 155–161.
Litvin, S.W., Goldsmith, R.E., Pan, B., 2008. Electronic word-of-mouth in hospitality and tourism management. Tour. Manage. 29 (3), 458–468.
Loh, S., Lorenzi, F., Saldaña, R., Licthnow, D., 2003. A tourism recommender system based on collaboration and text analysis. Informat. Technol. Tour. 6 (3), 157–165.
Lu, Y., Zhao, L., Wang, B., 2010. From virtual community members to C2C e-commerce buyers: Trust in virtual communities and its effect on consumers' purchase intention. Electron. Commer. Res. Appl. 9 (4), 346–360.
Lukins, S.K., Kraft, N.A., Etzkorn, L.H., 2008. Source code retrieval for bug localization using latent dirichlet allocation, 2008 15th Working Conference on Reverse Engineering. IEEE, pp. 155-164.
Mahakata, S., Tsokota, T., Mupfiga, P., Chikuta, O., 2017. A framework for enhancing Information Sharing and Collaboration within the Tourism Industry in Zimbabwe.
Mupfiga, P.S., 2015. Adoption of ICT in the tourism and hospitality sector in Zimbabwe. Int. J. Eng. Sci. 4 (12), 72–78.
Neuburger, L., Egger, R., 2020. Travel risk perception and travel behaviour during the COVID-19 pandemic 2020: a case study of the DACH region. Curr. Issu. Tour. 1–14.
Nezakati, H., Amidi, A., Jusoh, Y.Y., Moghadas, S., Aziz, Y.A., Sohrabinezhadtalemi, R., 2015. Review of social media potential on knowledge sharing and collaboration in tourism industry. Proced.-Soc. Behav. Sci. 172 (27), 120–125.
Nilashi, M., Ahani, A., Esfahani, M.D., Yadegaridehkordi, E., Samad, S., Ibrahim, O., Sharef, N.M., Akbari, E., 2019a. Preference learning for eco-friendly hotels recommendation: A multi-criteria collaborative filtering approach. J. Cleaner Prod. 215, 767–783.
Nilashi, M., Bagherifard, K., Rahmani, M., Rafe, V., 2017. A recommender system for tourism industry using cluster ensemble and prediction machine learning techniques. Comput. Ind. Eng. 109, 357–368.
Nilashi, M., bin Ibrahim, O., Ithnin, N., Sarmin, N.H., 2015. A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA–ANFIS. Electron. Comm. Res. Appl. 14(6), 542-562.
Nilashi, M., Ibrahim, O., Bagherifard, K., 2018a. A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. Expert Syst. Appl. 92, 507–520.
Nilashi, M., Ibrahim, O., Yadegaridehkordi, E., Samad, S., Akbari, E., Alizadeh, A., 2018b. Travelers decision making using online review in social network sites: A case on TripAdvisor. J. Computat. Sci. 28, 168–179.
Nilashi, M., Mardani, A., Liao, H., Ahmadi, H., Manaf, A.A., Almukadi, W., 2019b. A hybrid method with TOPSIS and machine learning techniques for sustainable development of green hotels considering online reviews. Sustainability 11 (21), 6013.
Nilashi, M., Yadegaridehkordi, E., Ibrahim, O., Samad, S., Ahani, A., Sanzogni, L., 2019c. Analysis of Travellers' Online Reviews in Social Networking Sites Using Fuzzy Logic Approach. Int. J. Fuzzy Syst. 21 (5), 1367–1378.
Pan, B., Fesenmaier, D.R., 2006. Online information search: vacation planning process. Ann. Tour. Res. 33 (3), 809–832.
Park, D.-H., Lee, J., Han, I., 2007. The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. Int. J. Electron. Comm. 11 (4), 125–148.
Qi, T., 2015. Research on Factors Influencing the Sharing Intention in Social Media———A model of Sina Weibo, International Conference on Logistics Engineering, Management and Computer Science (LEMCS 2015). Atlantis Press.
Redner, R.A., Walker, H.F., 1984. Mixture densities, maximum likelihood and the EM algorithm. SIAM Rev. 26 (2), 195–239.
Ricci, F., Werthner, H., 2001. Case base querying for travel planning recommendation. Informat. Technol. Tour. 4 (3–4), 215–226.
Rosen, D.L., Olshavsky, R.W., 1987. A protocol analysis of brand choice strategies involving recommendations. J. Consum. Res. 14 (3), 440–444.
Santos, F., Almeida, A., Martins, C., Oliveira, P., Gonçalves, R., 2016. Tourism Recommendation System based in user's profile and functionality levels. In: Proceedings of the Ninth International C* Conference on Computer Science & Software Engineering, pp. 93–97.
Shome, S., 2020. Intentions to use travel eWOM: mediating role of Indian urban millennials' attitude. Int. J. Tour. Cities.
Song, H., Liu, H., 2017. Predicting tourist demand using big data, Analytics in smart tourism design. Springer 13–29.
Sparks, B.A., Browning, V., 2011. The impact of online reviews on hotel booking intentions and perception of trust. Tour. Manage. 32 (6), 1310–1323.
Statista, 2020a. https://www.statista.com/statistics/658819/inbound-tourism-forecast-in-the-netherlands/.
Statista, 2020b. https://www.statista.com/statistics/1101300/coronavirus-cases-in-netherlands/.
Statista, 2020c. https://www.statista.com/topics/5524/social-media-in-the-netherlands/.
Teixeira, T., Kornfeld, L., 2013. Managing Online Reviews on TripAdvisor.
Tham, A., Croy, G., Mair, J., 2013. Social media in destination choice: Distinctive electronic word-of-mouth dimensions. J. Travel Tour. Market. 30 (1–2), 144–155.
Tsao, W.-C., Hsieh, M.-T., Shih, L.-W., Lin, T.M., 2015. Compliance with eWOM: The influence of hotel reviews on booking intention from the perspective of consumer conformity. Int. J. Hospital. Manage. 46, 99–111.
Ukpabi, D.C., Karjaluoto, H., 2018. What drives travelers' adoption of user-generated content? A literature review. Tour. Manage. Perspect. 28, 251–273.
Wattanacharoensil, W., Schuckert, M., Graham, A., Dean, A., 2017. An analysis of the airport experience from an air traveler perspective. J. Hospital. Tour. Manage. 32, 124–135.
Xiang, Z., Gretzel, U., 2010. Role of social media in online travel information search. Tour. Manage. 31 (2), 179–188.
Ye, Q., Law, R., Gu, B., 2009. The impact of online user reviews on hotel room sales. Int. J. Hospital. Manage. 28 (1), 180–182.
Yochum, P., Chang, L., Gu, T., Zhu, M., 2020. Linked open data in location-based recommendation system on tourism domain: A survey. IEEE Access 8, 16409–16439.
Yoo, K.-H., Lee, Y., Gretzel, U., Fesenmaier, D.R., 2009. Trust in travel-related consumer generated media. Informat. Commun. Technol. Tour. 2009, 49–59.
Zaheer, N., Trkman, P., 2017. An information sharing theory perspective on willingness to share information in supply chains. The. Int. J. Logist. Manage.
Zeng, B., Gerritsen, R., 2014. What do we know about social media in tourism? A review. Tour. Manage. Perspect. 10, 27–36.