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EXPLORING FACEBOOK USER RESPONSE TO COVID-19 VACCINATION PROGRAMME WITH SENTIMENT ANALYSIS AND TOPIC MODELLING

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ABSTRACT

In response to the COVID-19 pandemic, the Malaysian government has implemented the National COVID-19 Immunisation Programme. However, little research has been published on the perceptions of Malaysians regarding the vaccination programme. This study aims to (1) analyse the sentiment analysis of Facebook user perceptions using a Support Vector Machine and (2) identify the topics associated with the introduction of a COVID-19 vaccination programme in Malaysia for each sentiment. Facepager software was used to retrieve all vaccine-related comments. The R software was subsequently utilised for data cleaning and analysis. A linear Support Vector Machine regression model was used to classify the data into negative, neutral, and positive sentiments through sentiment analysis. To accomplish community detection in semantic network analysis and identify the topics for each sentiment, a clustering technique based on the Louvain method was employed. From a total of 5055 comments, 3269 (64.62%) are categorised as negative, followed by 1068 (21.11%) as positive, and 722 (14.27%) as neutral sentiment. The most discussed topics for negative-, positive- and neutral-sentiment were the negative effects of vaccines (74.9%), concern on vaccine adverse effects (69.0%), and lack of confidence (53.1%), respectively. The study findings can aid the local government and agencies to timely address public concern on COVID-19 vaccines.

Keywords: COVID-19 vaccine, sentiment analysis, topic modelling, machine learning, social media

1.0 INTRODUCTION

The severe acute respiratory syndrome coronavirus 2, also known as coronavirus disease 2019 (COVID-19), has recently brought a huge impact on the entire world. This disease that affects the respiratory tract is caused by a novel coronavirus (Jay Narayan Shah et al., 2020). Mild symptoms are common among infected individuals, and they often recover. However, some of them have the potential to get severe infections that cause breathing difficulties, low blood oxygen saturation, and even respiratory and multiple organ failure. As the number of infected people and deaths caused by COVID-19 escalated worldwide, on January 30, 2020, the World Health Organization (WHO) declared this disease a global public-health emergency (Ciotti et al., 2020; Cucinotta & Vanelli, 2020).

In Malaysia, a total of 2.76 million confirmed cases with almost 31,500 fatalities have been claimed by the COVID-19 pandemic up to January 31, 2021 (Mathieu et al., 2020). Consequently, the Malaysian Ministry of Health (MOH) and government have adopted various steps to safeguard

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citizens' health such as health screening at all points of entry, nationwide lockdown known as the Movement Control Order (MCO), and compulsory quarantine for all Malaysians and visitors returning from overseas (Shah et al., 2020). The latest initiative to curb the disease transmission chain was the Malaysian National COVID-19 Immunization Programme (NIP) (Schaffer DeRoo et al., 2020). The aim of this programme is to ensure that at least 80% of Malaysia's adult population receive vaccines by February 2022 to minimise the disease transmission, hospitalisation and death (The Special Committee For Ensuring Access To COVID-19 Vaccine Supply (JKJAV), 2021). However, NIP did not receive strong support from the public after its' launch in February 2021 due to rising issues on safety, misperception and illogical theory surrounding COVID-19 vaccines (Kricorian et al., 2022; Leng et al., 2021).

People's lack of knowledge and scepticism regarding the safety of vaccines may be one possible explanation for most concerns. Due to insufficient testing, they are concerned that the vaccine may cause long-term, chronic diseases. Another possible explanation is the dissemination of false information about COVID-19 via social media. This misinformation may persuade those who are hesitant or sceptical about the vaccine to oppose it, resulting in suboptimal vaccination rates (Zhang et al., 2021). In the age of technology, people can access a multitude of information via the Internet. This data regarding COVID-19 vaccinations might or might not be accurate, thus, resulted in many different perceptions (Yin et al., 2022). In addition, as of January 2022, there were 30.25 million social media users in Malaysia, of which 21.70 million had Facebook profiles (Digital 2022, 2022). It demonstrates the significance of Facebook as a platform for the dissemination of information and topics discussion. Therefore, it is imperative to assess public sentiments on COVID-19 vaccines via Facebook platforms to explore and identify people's attitudes towards vaccines. Thus, the aim of this analysis is to examine the sentiment and topic modelling encircling the COVID-19 vaccination programme on social media platform.

2.0 METHODOLOGY

For this study, vaccine-related data were collected from Facebook. Facebook was chosen because this platform commonly used for family and community interaction, and the majority of Facebook users are knowledgeable and literate adult (Yang & Lee, 2020). To acquire data, we began by creating an Application Programming Interface (API) account on Facebook and linking it to our Facebook account. Second, all comments posted at https://bit.ly/3dLeLmY and https://bit.ly/3xjaG1j were extracted using Facepager software version 4.3 (Jünger & Keyling, 2020) by executing the Facebook API authentication procedure. The MOH posted these two URLs on its official social media site Facebook on December 21, 2020, in order to survey acceptance or refusal of a COVID-19 vaccination programme. From December 21 through December 31, 2020, a total of 7107 comments were downloaded and become dataset for current analysis.

2.1 Data Preparation

After data collection, RStudio 4.1.3 software was used for data preparation and analysis, including sentiment analysis and semantic network analysis (Allaire, 2012). First, the duplicate remarks in the raw data were examined and removed. Second, the 'tm' package was used to remove unnecessary data such as emoticons, symbols, numbers, punctuation '@', special characters, and spaces, as well as any Facebook comment containing "www", "https://", URL," or "@username" (Ibrahim & Yusoff, 2015). Thirdly, all the comments were converted from uppercase to lowercase so that the subsequent analysis would not be affected by the loss of essential information (Rashid et al., 2013). According to the *Panduan Singkatan Khidmat Pesanan Ringkasan (SMS) Bahasa Melayu* (Dewan Bahasa dan Pustaka, 2008) and the 'malaytextr' package (Zahier, 2023), the text was stemmed to combine similar words into one. Due to the limitation of stop words in the Malay version, stop words were manually listed by evaluating the significance of each word. Subsequently, any word found in the dataset that was listed in the stop words were removed.

2.2 Sentiment Analysis

Sentiment analysis involves analysing people's attitudes, opinions, emotions, evaluations, and assessments of diverse entities, such as topics, events, issues, products, services, individuals, organisations, and their characteristics (Budiharto & Meiliana, 2018). The sentiment analysis was conducted by combining two approaches: a lexicon-based approach utilising SentiLexM (Tan et al., 2016) and a supervised machine learning approach utilising the 'e1071' package. An annotator manually classified each original comment as -1 (negative sentiment), 0 (neutral sentiment), or 1 (positive sentiment) based on its content. To accurately determine the sentiment of each comment, the code provided by the annotator was compared with lexicon-based code. Finally, all remarks with identical results were retained and the supervised machine learning method was implemented.

The linear support vector machine (SVM) regression model was subsequently conducted on a total of 3169 comments. The SVM was frequently implemented in practise with associated learning algorithms and effective text classification techniques (Silge & Hvitfeldt, 2022). Specifically, the linear SVM model performed better than other SVM models at classifying the data into negative, neutral, and positive sentiments (Ramasamy et al., 2021). In order to execute the SVM model, the data was divided into a training set of 70% (2,218 comments) and a testing set of 30% (951 comments). The Kappa test was utilised to examine the agreement between the three actual classes of sentiment and the three predicted classes of sentiment in the testing set. A kappa value greater than 0.61 is regarded as a good level of agreement (Ramasamy et al., 2021). To test the relationship between each word and these three classes of sentiment, Pearson's chi-square test was employed with p-value was less than 0.05 indicates significant relationship (Lang & Secic, 2006). Subsequently, using the 'wordcloud' package, all words by sentiment were displayed as a word cloud.

2.2 Topic Modelling

The clustering technique was conducted using the Louvain method by accomplishing community detection in semantic network analysis for each sentiment (Blondel et al., 2008). The Louvain method is highly efficient for detecting communities in both static and dynamic networks (Sarmento et al., 2016). A two-step approach was performed. In step 1, the semantic network was generated using two crucial components: nodes and edges. A node represents a word, while an edge represents word pairs or words linked within three words (Featherstone et al., 2020). In this analysis, neither word order nor direction were considered. The 'tidytext' and 'tidyr' packages were utilised to convert text to word pairings, whereas the 'igraph' package was utilised to calculate the degree and eigenvector centrality. In step 2, after generating the semantic network, the Louvain method was conducted to find the communities. In addition, only the top 75 words for each sentiment were included in the analysis of semantic networks.

3.0 RESULTS

In this study, the linear SVM model's accuracy was extremely high at 99.9%, with a 95% confidence interval extending from 92.3% to 100% and a kappa value of 0.89. In contrast, a lexicon-based approach utilising SentiLexM achieved only 63.9% accuracy, with a 95% confidence interval ranging from 62.6% to 65.2% and a Kappa value of 0.30. To conduct sentiment analysis and topic modelling, the linear SVM model has been selected. In total, 5059 comments were predicted for the three-sentence group. Among all the comments, 3269 were classified as negative sentiment (64.62%), 1068 as positive sentiment (21.11%), and 722 as neutral sentiment (14.27%).

3.1 Sentiment Analysis

The sentiment analysis revealed that 24,576 words were associated with the COVID-19 vaccination programme. Table 1 shows the top 15 words used on the COVID-19 immunisation programme across all types of sentiment. Of this, five most frequently used words were *tolak* (reject; 7.71%), *vaksin* (vaccine; 6.64%), *tidak* (no; 6.51%), *terima* (accept; 3.17%), and *dahulu* (first; 3.01%). The top five words with the highest percentage of usage for negative sentiments were *tolak* (reject; 10.87%), *tidak* (no; 7.66%), *covid* (covid; 1.63%), *mati* (die; 1.39%), and *takut* (fear; 1.39%). *Dahulu* (first; 8.27%), *vaksin* (vaccine; 8.24%), *menteri* (minister; 5.51%), *suntik* (inject; 3.53%), and *uji* (test; 3.33%) were the top five words with the highest percentage associated with neutral sentiment. For positive sentiment, the frequently use words were *terima* (accept; 10.61%), *baik* (excellent; 5.39%), *setuju* (agree; 3.20%), *selamat* (safe; 2.37%), and *rakyat* (people; 2.17%).

In the comparison cloud, each term on the COVID-19 vaccination programme represents a negative, neutral, or positive sentiment. Figure 1 demonstrates that the larger a word is, the more frequently it appears in Facebook user remarks.

Table 1 Top 15 words by sentiment

Malay Word	**English Word**	**Total**	**Negative Sentiment**	**Neutral Sentiment**	**Positive Sentiment**	***p*-value[a]**
		***n* (%)**	***n* (%)**	***n* (%)**	***n* (%)**	
tolak	reject	2,181 (7.71)	2,078 (10.87)	46 (1.42)	57 (0.96)	<0.001
vaksin	vaccine	1,879 (6.64)	1,279 (6.69)	266 (8.24)	334 (5.62)	<0.001
tidak	no	1,840 (6.51)	1,464 (7.66)	163 (5.05)	213 (3.59)	<0.001
terima	accept	896 (3.17)	177 (0.93)	89 (2.76)	630 (10.61)	<0.001
dahulu	first	851 (3.01)	386 (2.02)	267 (8.27)	198 (3.33)	<0.001
menteri	minister	538 (1.90)	233 (1.22)	178 (5.51)	127 (2.14)	<0.001
rakyat	people	477 (1.69)	278 (1.45)	69 (2.14)	130 (2.19)	<0.001
suntik	inject	472 (1.67)	286 (1.50)	114 (3.53)	72 (1.21)	<0.001
baik	good	442 (1.56)	108 (0.57)	14 (0.43)	320 (5.39)	<0.001
uji	test	434 (1.53)	242 (1.27)	108 (3.34)	84 (1.41)	<0.001
covid	covid	418 (1.48)	311 (1.63)	44 (1.36)	63 (1.06)	0.006
mati	die	278 (0.98)	266 (1.39)	1 (0.03)	11 (0.19)	<0.001
takut	afraid	258 (0.91)	253 (1.32)	0 (0.00)	5 (0.08)	<0.001
setuju	agree	248 (0.88)	52 (0.27)	6 (0.19)	190 (3.20)	<0.001
selamat	safe	225 (0.80)	83 (0.43)	1 (0.03)	141 (2.37)	<0.001

Note: [a]Pearson's chi-squared test.

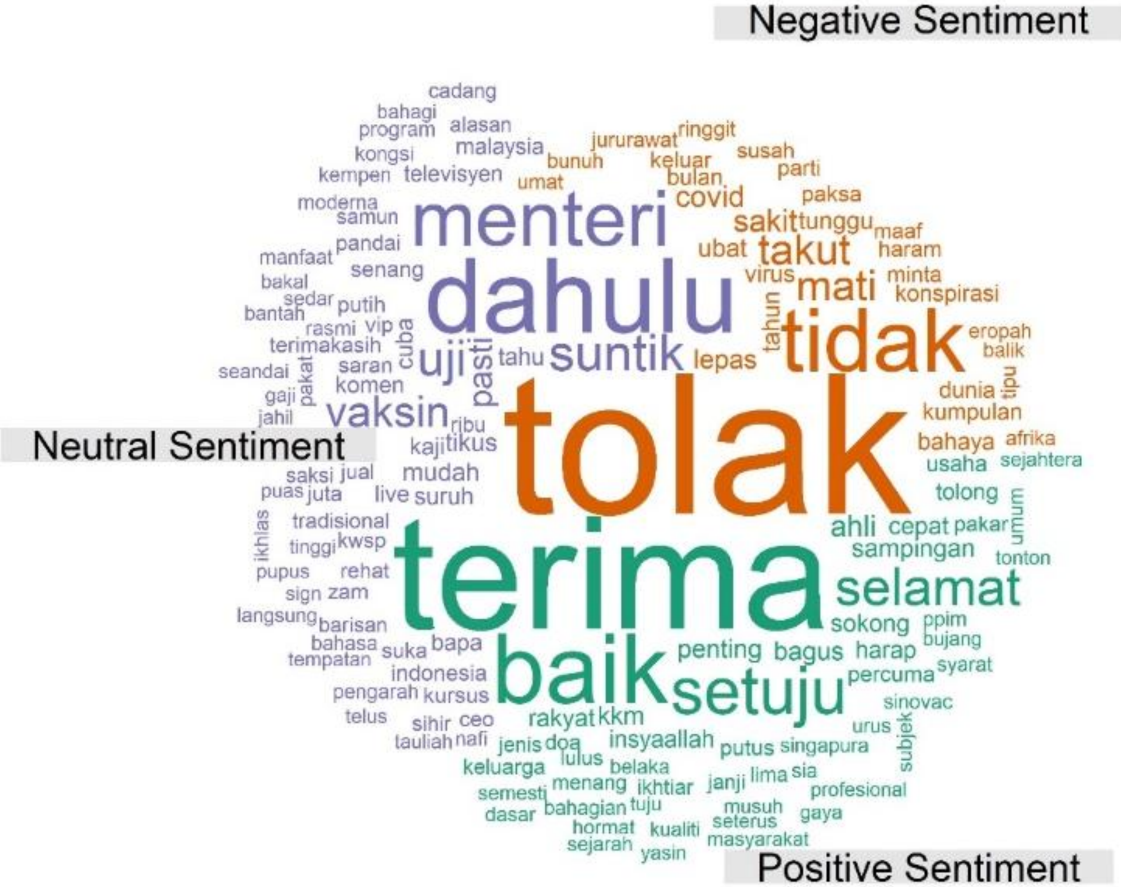

Figure 1. Wordcloud on COVID-19 vaccination program by negative, neutral and positive sentiment

3.2 Topic Modelling

The topics discussed by Facebook users in Malaysia were identified based on community detection using the Louvain method. Three topics were identified for both negative and neutral sentiment, and two for positive sentiment. In general, there were a total of 21017 occurrences of all sentiments, with 14207 occurrences of negative sentiment, 2040 occurrences of neutral sentiment, and 4770 occurrences of positive sentiment.

Table 2 reveals that the negative effects of vaccines received the most attention for negative sentiment (74.9%), followed by distrust in government (23.2%) and concern about adverse effects (1.9%). Furthermore, when discussing on topic of negative effects of vaccines, most of the *vaksin* (vaccine) words were related to *tidak* (no), *tolak* (reject), *mati* (die), and *takut* (afraid) with a total of 1504 occurrences, and the *tidak* (no) word was related to *tahu* (know) with 206 occurrences. This indicates that most of the Facebook users' comments regarding vaccination rejection were because they do not know much about it and afraid the vaccine can cause death.

The sentiment analysis also showed that most of the *dahulu* (first) words were related to *menteri* (minister), *uji* (test), *politik* (politic), and *suntik* (inject), with a total of 508 occurrences. This reflects on the recommendation from the Facebook users on testing and injecting the politicians (176 occurrences) first before distributing vaccine to the public. Concerning adverse effects, the majority of *kesan* (effect) words were related to *sampingan* (side), *bukti* (evidence), and *mutasi* (mutation) with a total of 131 occurrences, indicating that Facebook users suggestion to get proof of no side effects or mutations within one year after vaccination (42 occurrences).

Table 2 Top 15 word associations for negative sentiment

Topic[a]	From		To		*n* (%)
Negative effects of vaccines					**10,640 (74.9)**
	tidak	(no)	*vaksin*	(vaccine)	837
	tolak	(reject)	*vaksin*	(vaccine)	349
	tidak	(no)	*tahu*	(know)	206
	vaksin	(vaccine)	*mati*	(die)	171
	vaksin	(vaccine)	*takut*	(afraid)	147
Distrust in government					**3,296 (23.2)**
	politik	(politic)	*ahli*	(member)	176
	dahulu	(first)	*menteri*	(minister)	161
	dahulu	(first)	*uji*	(test)	122
	dahulu	(first)	*politik*	(politic)	121
	dahulu	(first)	*suntik*	(inject)	104
Concern about adverse effects					**271 (1.9)**
	kesan	(effect)	*sampingan*	(side)	103
	tahun	(year)	*satu*	(one)	42
	kesan	(effect)	*bukti*	(evidence)	20
	satu	(one)	*salah*	(wrong)	11
	kesan	(effect)	*mutasi*	(mutation)	8

Note: [a]The topic was created based on community detection using Louvain method;
Malay Word (English Word).

In terms of neutral sentiment, Table 3 reveals that the most prevalent topic was lack of confidence (53.1%), followed by distrust in the government (46.3%), and pharmaceutical conspiracies (0.6%). Specifically, most of the *vaksin* (vaccine) words related to *tidak* (no), *terima* (accept), *covid* (covid), *tolak* (reject), and *kesan* (effect) with a total of 224 occurrences, indicating that the majority of Facebook users are unsure (36 occurrences) whether to reject or accept (69 occurrences) the COVID-19 vaccine due to the upcoming effect. Concerning distrust in government, most Facebook users with neutral sentiment have the same conversation as Facebook users with negative sentiment (403 occurrences). Regarding the pharmaceutical conspiracy topic, the majority of *tikus* (rat) words (12 occurrences) were related to *makmal* (lab) and *hidup* (alive), indicating that Facebook users view themself as lab rat experiments to receive new COVID-19 vaccines.

Table 3 Top 12 word associations for neutral sentiment

Topic[a]	From		To		*n* (%)
Distrust in government					**945 (46.3)**
	dahulu	(first)	*menteri*	(minister)	151
	dahulu	(first)	*uji*	(test)	85
	dahulu	(first)	*suntik*	(inject)	73
	menteri	(minister)	*suntik*	(inject)	47
	menteri	(minister)	*uji*	(test)	47
Lack of confidence					**1,083 (53.1)**
	vaksin	(vaccine)	*tidak*	(no)	85
	tidak	(no)	*terima*	(accept)	69
	vaksin	(vaccine)	*terima*	(accept)	56
	tidak	(no)	*pasti*	(sure)	36
	vaksin	(vaccine)	*covid*	(covid)	33
	vaksin	(vaccine)	*tolak*	(reject)	26
	tidak	(no)	*tahu*	(know)	24

	vaksin	(vaccine)	*kesan*	(effect)	24
Pharmaceutical conspiracy					**12 (0.6)**
	tikus	(mouse)	*makmal*	(lab)	10
	tikus	(mouse)	*hidup*	(alive)	2

Note: [a]The topic was created based on community detection using Louvain method;
Malay Word (English Word).

For positive sentiment, the frequently discussed topics were concern about adverse effects (69.3%) and distrust in government (30%). Additionally, majority of Facebook users with positive sentiment have the same discussion topic as of users with negative sentiment, although their perspective was different. This suggests that many Facebook users with positive sentiment will accept the vaccines by MOH (160 occurrences) but reject it (98 occurrences) if the vaccine unsafe or caused side effect (173 occurrences). On topic of distrust in government, the Facebook users with positive sentiment have the same discussion as the users with negative and neutral sentiment on suggestion to test and inject politicians before implementing to the public (67 occurrences).

Table 4 Top 15 word associations for positive sentiment

Topic[a]	**From**		**To**		***n* (%)**
Concern about adverse effects					**3,306 (69.3)**
	terima	(accept)	*vaksin*	(vaccine)	110
	vaksin	(vaccine)	*tidak*	(no)	98
	vaksin	(vaccine)	*kesan*	(effect)	68
	vaksin	(vaccine)	*selamat*	(safe)	61
	tidak	(no)	*selamat*	(safe)	60
	terima	(accept)	*tidak*	(no)	58
	vaksin	(vaccine)	*kkm*	(moh)	50
	kesan	(effect)	*sampingan*	(side)	45
Distrust in government					**1,464 (30.7)**
	ahli	(member)	*politik*	(politic)	106
	dahulu	(first)	*menteri*	(minister)	106
	baik	(good)	*dahulu*	(first)	80
	baik	(good)	*rakyat*	(people)	67
	dahulu	(first)	*ahli*	(member)	58
	dahulu	(first)	*politik*	(politic)	58
	baik	(good)	*menteri*	(minister)	51

Note: [a]The topic was created based on community detection using Louvain method;
kkm (moh) = Kementerian Kesihatan Malaysia (Ministry of Health Malaysia);
Malay Word (English Word).

4.0 DISCUSSION

To the best of author's knowledge, this is among the first study conducted on Facebook user's perception towards COVID-19 vaccination programme using SVM method in Malaysia. Based on the sentiment and topic modelling, the predominant sentiment among Malaysian Facebook users towards COVID-19 vaccine was negative (64.62%). The terms *tolak* (reject) and *tidak* (no) indicated that public were not in agreement with the MOH on vaccination programmes. This study finding is in line with a recent study conducted in Türkiye that found similar rejection towards COVID-19 vaccines (Özceylan et al., 2020). Interestingly, the primary reason for the rejection of vaccines in Türkiye was related to issue of mistrust with vaccination companies.

Majid and Ahmad's (2020) also have conducted a systematic review on COVID-19 vaccines rejection and found multiple contributing factors such as previous bad experience, improper treatment by healthcare providers, questionable source of information, distrust on the health system, and complexity of policy.

Social media platforms (such as Twitter, Facebook, and Instagram) facilitate communication. On these platforms, users can freely post, comment, express their opinions on specific topics, and communicate with others (Jiang et al., 2019). Therefore, the discussions of the COVID-19 vaccine on social media serve as a source of information for determining people's concerns regarding the vaccine. This study found that the frequently discussed topics among the Facebook users were negative effects (74.9%), concern about adverse effects (69.3%) and lack of confidence (53.1%) in the governments' vaccine programme which is consistent with some findings from previous research (Ahmad et al., 2017; Chan et al., 2018; Harmsen et al., 2013; Rumetta et al., 2020; Syiroj et al., 2019). These findings can be used by the relevant authorities to timely response public's concern on COVID-19 vaccine. For instance, as many people have more discussions about side effects of vaccination on social media platforms, more publicity can be conducted to inform the public about the symptoms of side effects, how to alleviate them, and how to handle emergency situations. Eventually, the prompt response to people's concerns can increase public's confidence and encourage vaccination.

5.0 CONCLUSION

In conclusion, this paper presented an analysis of sentiment analysis and topic modelling of Facebook comments regarding COVID-19 vaccines. Based on the current findings, it is essential for the MOH and local governments to address all publics' concern on COVID-19 vaccine in timely manner to eliminate any misunderstandings and improve vaccination rate.

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