Analysis of Selective Exposure Cluster in the Covid-19 Vaccine Information Network on Twitter

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Abstract. The purpose of this study was to identify clusters formed in the Twitter network related to the topics of the Covid-19 vaccine. This study uses a quantitative approach with social network analysis with selective exposure cluster method. The population of this study is the use of the Twitter social network with the keyword "covid-19 vaccine" as a cluster sample. Data is collected using the NodeXL application. The data were analyzed by grouping based on the Clauset-Newman-Moore algorithm cluster by calculating the entire network of users, the level of hubs in the cluster, grouping in the network, finding the highest twitter network. The results showed that official government accounts, political figures, and mass media simultaneously appeared in all data sets so that they formed a cluster that consistently supported the success of the national vaccination program.

Keywords: cluster · selective exposure · information network · covid-19 vaccine · twitter

1 Introduction

In early March 2021, the Indonesian government officially announced the first patient with COVID-19. The government has carried out various policies to control the spread of this disease. Starting from PSBB, the new normal, and vaccination policy. Regarding vaccination policy, of course, there are pros and cons where we can find this both in the real world and in the virtual world. We can find discussions regarding the COVID-19 vaccine on various social media platforms, and here we choose Twitter. Twitter itself can be a public space or echo chamber for its users. In this case, we assume that there has been "information homophily" forming an echo-chamber space which we will analyze using selective exposure theory.

Various information on Twitter can be in facts or vice versa. Especially during a crisis like today, where uncertainty needs to be faced wisely. Moreover, the amount of information milling about on social media is quite difficult to identify whether the information is a fact or a lie. Moreover, according to the Katadata report, Indonesian people are still relatively low at the level of the information literacy sub-index [1]. It can then explain how easily information can be disseminated through various social media platforms.

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This information can potentially influence public perception in responding to information circulating on Twitter related to the effectiveness of vaccines [2]. Moreover, with the role of the buzzer, which seems to support and blindly defend government policies from criticism from other users in a counter-productive way, it can potentially form information polarization during a pandemic [3]. Even in times of crisis, ideally, people should have the same perception and work together to get out of the pandemic. However, it is undeniable that the presence of the internet today makes the current flow of information very difficult to stem. So to respond to this, ideally, the community as social media users need to be critical of any information they consume.

However, the fact is that Twitter users selectively consume information according to subjective preferences. For example, it can be seen in the behavior of a person selectively choosing which people to follow. It happens because of the tendency to choose information to strengthen opinions while avoiding information or different opinions. This phenomenon became known as selective exposure. Cognitive dissonance theory proposed by Festinger and Uses and Gratification is often used to understand this phenomenon [4].

The motive for this selective exposure cannot be separated from the role of the partisan media. In addition, the presence of factors such as who conveys the message and certain conditions also influence a person's attitude in consuming information [5], and the beneficial consequences of the selected information also contribute to the motive for selective exposure [6].

In addition, the features of digital service providers that allow for personalization can allow algorithms to work to recommend information based on their likes, people they follow, last read news, and various other forms of personalization. It is known as a filter bubble [7].

There are several previous studies related to the phenomenon of selective exposure. First, the research conducted by Knobloch et al. [8] discusses the success of health message campaigns that are also influenced by the beliefs or habits of individuals [8]. Second, the research conducted by Prastyo et al. [9] studied the relationship between cognitive dissonance and selective exposure among female commercial sex workers (CSWs) [9]. Third, Anggarini [10] examines the choice of informants' information sources that are influenced by needs and desires (U&G Theory) in obtaining information related to COVID-19 [10]. Fourth, Himelboim et al. [11] examined the network of conversations that occurred on Twitter regarding the human papillomavirus (HPV) vaccine [11]. The information network then forms a cluster which will be used to analyze the interaction flow and information that can be implemented in studying selective exposure.

In contrast to previous studies, this study uses clusters to analyze the flow of information on Twitter related to the Sinovac Vaccine. It was different from the research conducted by Knobloch et al. [8], Prastyo et al. [9], and Anggarini [10], which used the individual as the level of analysis in understanding selective exposure. Furthermore, this study has several similarities with the study conducted by Himelboim et al. [11], which used clusters to analyze selective exposure. However, in contrast to the planned research, the researcher will use digital data for Twitter users in Indonesia.

In addition, previous studies related to selective exposure carried out, especially in Indonesia, still use traditional methods where methods such as surveys, experiments,

and interviews are the methods commonly used in studying this phenomenon. However, along with the development of information and communication technology such as social media, the traditional approach encounters several obstacles in managing and analyzing social media data (digital data). According to Laney, digital data (Big Data) has three characteristics, namely volume, velocity, and variety, so it requires another approach [12]. Based on this, the research plan will use big data, which will be coupled with social network analysis (SNA) as the basis of the method for analyzing selective exposure that occurs on Twitter. Social network analysis itself applies the field of network science that is applied to study human relationships and connections [13].

In general, selective exposure can be interpreted as a phenomenon in which people deliberately seek information that can support or strengthen previous beliefs and avoid information that contradicts their opinions [14]. According to Festinger [4] selective exposure is a central proposition in cognitive dissonance theory [4]. Cognitive dissonance is an uncomfortable feeling when faced with two cognitively contradictory things, thus motivating a person to reduce the dissonance and avoid things that can increase dissonance.

According to Festinger's [4] dissonance theory, selecting like-minded information can help people reduce dissonance. However, not all experiences of cognitive dissonance need to be reduced because people can temporarily forget their views. However, according to Festinger, selective exposure will emerge when faced with moderate dissonance. Furthermore, Festinger (1964) found that high self-confidence will inspire less selective exposure than less confident people [4, 15].

In the field of communication, selective exposure is a common explanation for why scholars are not finding more evidence of the power of media effects. According to Klapper in Freedman and Sears [14], selective exposure is an essential factor in determining the effectiveness of mass communication. Thus, according to Klapper in Stroud [16], the media tend to take on the role of strengthening attitudes rather than changing public attitudes [16]. Furthermore, according to McGuire and Papageorgis [17] selective exposure is a form of public resistance to all persuasion messages received [17]. In searching for health information online, the phenomenon of selective exposure also appears when talking about high-risk diseases. Conflicts can arise from debates related to the effectiveness and health impacts of an offered treatment [18]. In this study, the use of the COVID-19 vaccine for COVID-19 disease. Lauckner & Hsieh in Liao [18] use the term "cyberchondria" to precisely describe the phenomenon of selective exposure that occurs in the search for health information in cyberspace. Cyberchondria refers to the escalation of people's medical problems after searching online for information. For example, search engines (such as Google) use algorithms to provide more "satisfactory" information to their users than providing accurate information. It can lead to the confirmation bias that could support prior beliefs. Furthermore, a tendency based on uncertainty can lead to wrong medical decisions.

There are several reasons why this research is necessary. First, the infodemic is a challenge for the success of the government and society in dealing with the spread of the COVID-19 virus. Second, the development of information related to the Sinovac vaccine, which is still growing, requires the government and all stakeholders to be more responsive to the development of public opinion. Third, maintaining public trust and

increasing self-efficacy are top priorities so that the government has a role in intervening in public health behaviour.

By understanding the information network formed, the research can provide cluster visualization. Each cluster is a representation of the public discourse that is happening. Analyzing the cluster can be seen who the key actors in a network are.

Then, interactions related to vaccination topics on Twitter, such as retweets, follow, and replies can form a "topic network" that we can use to understand the selective exposure phenomenon on Twitter. Our research aims to identify clusters that are formed based on a network of topics related to the corona vaccine.

2 Methods

2.1 Data

This study collects data (13–15 November 2021) on Twitter user activities related to the COVID-19 vaccine conversation in Indonesia. This period was chosen because of the discourse on giving vaccines to children during this period. Each dataset consists of user self-descriptive information (bio), tweet content, hashtags, hyperlinks, and relationships between users such as retweets, mentions, and replies. NodeXL software is used to collect data, analyze and visualize the network. In aggregate, the total collected dataset was 4,654 Twitter users using the queries "vaccination until: 2021-11-14 since: 2021-11-13" and "vaccination until: 2021-11-16 since: 2021-11-15". Finally, the collected dataset was calculated using the overall graph metrics, vertex in-degree, group metrics, and network top items features.

2.2 Network Analysis and Selective Exposure Clusters

Our researchers use network analysis to understand the phenomenon of selective exposure in the COVID-19 vaccination conversation topic network on Twitter [19]. This method originally was called selective exposure cluster. According to this method to identify selective exposure in this network we used cluster, hub consistency, and frequency use of hashtag, hyperlink, and mention. The use of complex network analysis to track conversations about certain vaccines on Twitter has become popular recently [11]. Therefore, NodeXL is used to calculate the matrix and visualize the network. Furthermore, the social network is built based on the available dataset, where users who post are nodes (or actors), and the relationships formed are edges (mentions, replies, and follows).

First, to identify the clusters we used the Clauset-Newman-Moore algorithm to identify network groups from groups of relatively more connected users in a given topic network, a cluster analysis tool available in NodeXL [13]. This algorithm is used because of its ability to analyze large network datasets and find subgroups efficiently. This algorithm uses an edge betweenness matrix to identify the boundaries of a community. Each user, then, was classified into the most suitable group (cluster) based on the interconnections between users. The distance between clusters was then measured based on the modularity threshold as follows [19]:

- Modularity value <0.4, then the distance between clusters is low.
- Modularity value is between 0.4–0.6, so the distance between clusters is moderate.
- Modularity value is >0.6, then the distance between clusters is high.

To simplify the analysis, we only use the majority of clusters that are considered to represent the entire topic network that will be selected.

Second, we identify a hub in a cluster with a look at the position of the hub in a network; usually, the hub's location is at the centre of the network. In addition, hubs can also be identified based on the number of direct relationships seen from the in-degree centrality matrix. Hub on Twitter can be interpreted as an influencer or celebtwit. Third, an analysis of the frequency of hashtags, hyperlinks, and mentions is carried out by taking an inventory of the highest frequency of usage of these three things in a cluster.

3 Result

We built a data set containing a collection of tweets related to the COVID-19 vaccination. Based on the maximum number allowed by the Twitter API, we collected a recent dataset ranging from 2,200 to 2,400 users who posted messages containing predefined keywords. The November 13 data set included 2,233 users, 959 connected by 2,083 unique relationships (e.g. follows, mentions, and replies). Furthermore, on November 14, the number of users discussing this topic decreased when there were only 78 users, 31 of them connected by 73 unique relationships. Finally, The November 15 data set included 2,343 users, 1.126 of them connected by 2,385 unique relationships. As discussed next, we mapped each data set based on the relationship among its users and applied network analysis to identify clusters and hubs (see Table 1).

3.1 Cluster in the COVID-19 Vaccination Topic Network

Based on the cluster analysis results using the Clauset-Newman-Moore algorithm, on November 13, four large clusters were found. The first cluster consisted of 233 users linked by 243 connections. The second one was composed of 129 users linked by 287 connections. The third cluster stands up for 92 users linked by 111 connections. The fourth cluster consisted of 88 users linked by 132 connections. These four significant clusters accounted for 56.5% of all connected users and 37.1% of all relationships in the network. The modularity value for this cluster is 0.51; this number indicates a moderate degree of separation between clusters.

Table 1. Collected data set from 13–15 November 2021

Period	Vertices	Connected component	Unique edges
13/11	2.233	959	2.083
14/11	78	31	73
15/11	2.343	1.126	2.385

Furthermore, the network formed on November 14 revealed one central cluster consisting of 29 users with 31 unique relationships. This primary cluster accounts for 93.5% of all connected users and 42.4% of all relationships in the network. The modularity value for this network is 0.59, which indicates that the separation rate is still moderate but close to the high separation rate (0.60) between clusters.

Finally, the network formed on November 15 revealed two main clusters. The first cluster consists of 834 users with 646 unique relationships and the second cluster consists of 660 users with 795 unique relationships. These two main clusters account for 132.6% of all connected users and 60.4% of all relationships in the network. The modularity value for this network is 0.40, which indicates a moderate degree of separation.

3.2 The Hub Consistency in Clusters

The findings show that conservatively pro-science accounts (they claim they only reject the corona vaccine based on their scientific data) consistently reject its mandatory use. This @tedhilbert account consistently appears as a hub in the cluster. The same data set on November 13–15 makes the clusters generally represent pro-science groups (see Figs. 1, 2, and 3). Furthermore, on November 13 and 15, the @jokowi account consistently appeared in the same cluster. This cluster was identified as a cluster that supports the success of the corona vaccination program in Indonesia.

Furthermore, the @geloraco account only appeared as a hub on November 13 (Fig. 1). On that date, the media reported a piece of news entitled "Menkes Budi Gunadi: We Thought Vaccination Could Solve the Covid-19 Pandemic". This news received a more significant response from anti-vaccine groups and conspiracy theorists; this can be seen from the number of responses (retweets and replies) to the news. Geloraco is an online news site but has not been registered with the Press Council. This media uses bombastic title writing techniques, and its news content often "attacks" the government.

Next, the @dinihrdianti account appeared as a hub on November 13 (Fig. 1). This account supports the government's vaccination policy by disseminating information related to vaccination and inviting people to continue to follow health protocols. This account represents a cluster that can generally be described as a group of digital troops (cyber troops) whose job is to amplify certain narratives, such as the vaccine success campaign.

Furthermore, on November 14, the @tedhilbert account actively disseminated information related to claims that suggested finding a partner (married) with those who had never had the corona vaccine injection and included a hyperlink https://investigasi.org/manipulation-data-ilmiah-to-justify-vaccination-children/. This information is then disseminated to certain people by mentioning other accounts, i.e. @Ariefmantoi, @BalagiDico, @AdilAdiany1, @MicMedsos, @el_lia05095930, @Inggar10892898, @eko_n9udiarto, @Alibaba, @Aznlova, @__Sridiana_3va, @LsOwien, @StopPlandemit, @Sgara4_Hfam_ProfessorZubairi, @Prof_Azyumardi, @GiaPratamaMD, @GundiDr, @dr_koko28, @DrSLSimonSpKK, @drpriono1, @dokoterapin, @AdamPrabata, @dr_tompi, and @AldoBabeh.

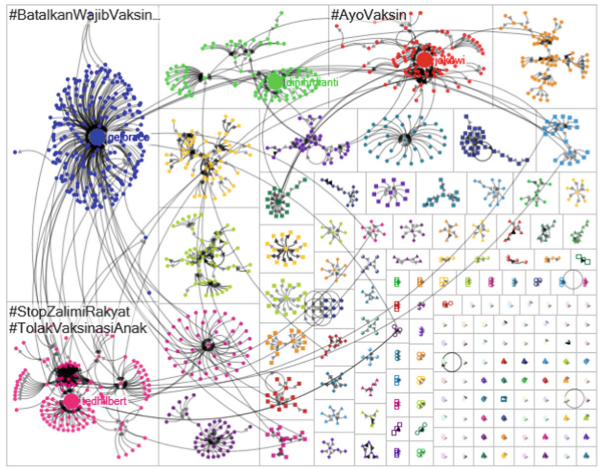

Fig. 1. The COVID-19 vaccination social network, November 13, 2021.

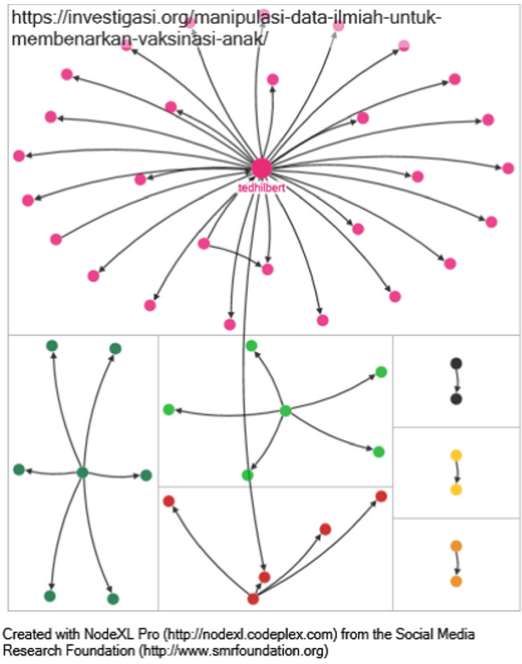

Fig. 2. The COVID-19 vaccination social network, November 14, 2021.

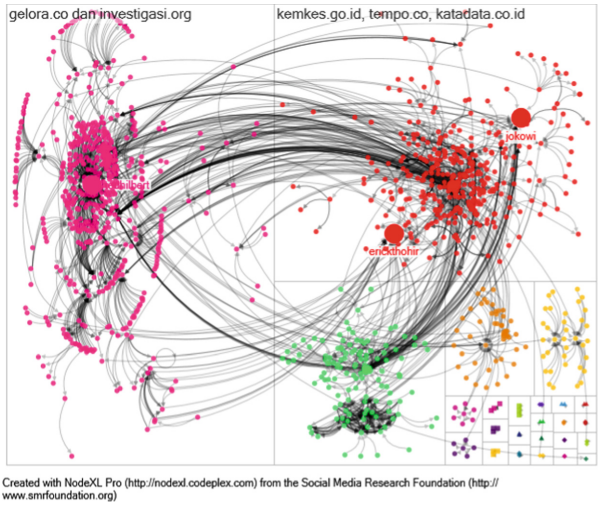

Fig. 3. The COVID-19 vaccination social network, November 15, 2021.

3.3 Frequency of Hashtag, Hyperlink, and Mention in Clusters

On November 13, four large clusters were identified, and from each cluster, a ranking was carried out based on hyperlinks used. In the opposition (sceptic) cluster, researchers found that the most frequently mentioned domain names were alternative online news media (gelora.co, used by 198 users) and user-generated content (twitter.com with 10 users). There are no other users mentioned in their social network in this cluster. The frequently used hashtags are #BatalkanWajibVaksinC19ANAK (as many as three users) and #vaccination (as many as two users).

In the second cluster, namely pro-science, researchers found the most frequently used domains were regional online news media (46 users used tandaseru.com), user-generated content (31 users used twitter.com), the independent online news media (times)..id used by 13 users). Furthermore, the top users most frequently@tedhilbert (15 users), @stopplandemit (15), Alibaba (14), aznlova (14), and @__sridiana_3va (14). The hashtag used most frequently in this cluster was #CancelCompulsory VaccinationC19ANAK, with 25 users.

In the third cluster, the cyber troop cluster, the researchers found that the most frequently used domain was mainstream, namely detik.com, with 51 users. There are mentions of other users and the use of hashtags by users in this cluster.

Finally, in the fourth cluster, a mixed cluster between pro-government and pro-vaccine clusters, they found that the most frequently used domain is mainstream which is the same as the cyber troop cluster where 17 users use detik.com. Furthermore, the Twitter account @jokowi is the account with the most mentioned 57 times in this cluster. The most frequently used hashtags were #MandalikaMendunia by ten users and #ayovaksin by two users.

On November 14, only one cluster was identified, and each cluster was ranked based on the hyperlinks used. In this cluster, researchers found that the domain names most

often used as references are community-based websites such as investigation.org and medical journal websites such as cureus.com, which have the same frequency of use. The most @tedhilbert, each of which is mentioned@aldobabeh twice. There are no hashtags in this cluster.

On November 15, two large clusters were identified. In the first cluster, a hub identifies itself as pro-science. This cluster's most frequently used domains are the alternative online news website gelora.co (140) and the pro-science community-based website investigation.org (125). Furthermore, the most frequently@aldobabeh 33 times and @tedhilbert 30 times. The hashtags used the most were #COVID19 (40) and #ayovaksin (12). The emergence of hashtags in this cluster is because there are official government accounts such as @kemenkesri and @dkijakarta, and there are official online news accounts such as @infosolsel and @beritaminangcom.

The next cluster consists of the government and vaccine support cluster. The top domains most often used are official government websites (140), such as the website kemkes.go.id, setkab.go.id, and several official local government websites. In addition, domains such as co.id have a frequency of use of 102 times. This domain consists of websites based on data portals such as databoks.katadata.co.id and several online news media such as Republika.co.id. The most frequently@kemenkseri (27), kecgenteng (22), and the public relations division of the police (15). Finally, the hashtags used the most were #indonesiabebascovid 164 times and #IkhtiarAtasiPandemi 25 times.

4 Discussion and Conclusion

Based on the research results and indicators described previously, in general, there has been a phenomenon of selective exposure to Twitter users in the COVID-19 vaccine topic network. The existence of this cluster leads to fragmented information sources and interactions in a network. It is in line with the concept of homophily that can be used to explain the formation of this network. Overall, the network of topics formed is a type of inbreeding homophily relationship where the relationship is caused by the factor of similarity in belief (value homophily) so that each cluster has a different view and attitude in responding to the COVID-19 vaccine, especially in children.

Several factors cause the formation of this selective exposure cluster. Firstly, Twitter users associate themselves with beliefs or preferences for other people or sources of information that are in line with existing beliefs. Second, there is a user directional motivation factor in forming clusters in this topic network. The existence of this cluster makes it easier for users to consume narratives or content from people who are in the same cluster than people who are in other clusters.

Many clusters were identified during the data collection period, but only a few were observed and analyzed in this study. Based on the analysis during November 13–15, the cluster formed was divided into two groups, namely groups that supported and opposed giving COVID-19 vaccine to children. Although there were four majority clusters on November 13, on November 15, only two large clusters remained. @geloraco and @dinihrdianti are the hubs for their respective clusters, which later, on November 15, merged into two large clusters, where @geloraco to the COVID-19 anti-vaccine cluster and @dinihrdianti to the vaccine support cluster (government).

In the "pink" (reject) cluster, the majority of the hubs are users who identify themselves as pro-science who reject the mandatory vaccine, government opposition, and non-mainstream (gelora.co). In this cluster, most of the hubs are users who identify themselves as pro-science who reject the mandatory vaccine, government opposition, and minor independent media, such as Gelora. In addition, the hashtags that were used the most could be interpreted to refer to the group that refused the COVID-19 vaccine, especially against children (for example, #BatalkanWajibVaksinC19Anak), and the users who were most frequently mentioned (mentioned)were identified as people who refused the COVID-19 vaccine. In addition, in this cluster, the most frequently accessed website pages are also more diverse, such as an independent news portal website (gelora.co), a regional news portal (tandaseru.com), a public information service website managed by a foundation (investigasi.org), and the medical science journal website (cureus.com).

Furthermore, the "red" cluster differently describes a group with mixed exposure to information from both mainstream media organizations (tempo) and government institutions (ministry of health). The various hashtags and hyperlinks used can also be observed even though they have the same connotation. The difference between these two main clusters can be observed from the composition of the COVID-19 anti-vaccine cluster, which prefers alternative news media due to a distrustful attitude towards mainstream mass media.

The clusters formed in this "vaccination" topic network are very separate because they have a high modularity rate, even though they showed moderate modularity on November 15, 2021. Although these clusters are very separate and the percentage of relationships between clusters is low, this does not mean that there is no interaction between several clusters. It then shows that in addition to users on Twitter being primarily exposed to the content shared by "friends" in the same cluster, they also have limited potential to be exposed to content from other clusters. In other words, users on Twitter are not actively exposing themselves to various available sources of information. However, they may be indirectly exposed to content from various available sources.

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