

Sentiment Analysis of Facebook Posts through Special Reactions: The Case of Learning from Home in Indonesia Amid COVID-19

Ahmad R. Pratama

Department of Informatics, Universitas Islam Indonesia, Jl.Kaliurang Km 14.5, Sleman DIY 55584, Indonesia

ARTICLE INFO

Article history:

Received March 20, 2022
Revised April 11, 2022
Accepted April 21, 2022

Keywords:

Sentiment analysis;
Facebook posts;
special reactions;
CrowdTangle;
learning from home;
COVID-19

ABSTRACT

In contrast to several other countries, Indonesian sentiment analysis research is primarily focused on the text-based analysis of Twitter. Given that Twitter users in Indonesia account for less than a seventh of those on Facebook, sentiment analysis on the latter may have a greater impact than on the former. This research sought to close that gap in the literature by pioneering the use of Facebook special reactions as an alternative to text-based sentiment analysis on social media posts about Indonesian social issues. The topic of learning from home in the midst of the COVID-19 pandemic was chosen because it is both timely and relatable to almost everyone in the country. Through CrowdTangle, a total of 39,657 Facebook posts containing the key phrase “*belajar dari rumah*” were gathered, but only 9,310 of them received special reactions and thus remained to be analyzed quantitatively. The results indicated that with the exception of ‘love,’ all special reactions are somewhat correlated, suggesting that they can be used to indicate the negative valence of a Facebook post. Further analysis revealed a significant increase in the proportion of posts with a negative valence during the second year of the COVID-19 pandemic. The textual analysis of the posts revealed that those with a negative valence primarily discuss internet access and other IT infrastructure issues that presumably impede learning from home activities for some. The main contribution of this study is to demonstrate how to analyze special reactions on Facebook for sentiment analysis purposes, particularly in the context of Indonesia. Additionally, it lays out how Facebook’s special reactions have the potential to be used in conjunction with text-based sentiment analysis to provide a complete picture of the social issue being investigated.

This work is licensed under a [Creative Commons Attribution-Share Alike 4.0](https://creativecommons.org/licenses/by-sa/4.0/)



Corresponding Author:

Ahmad R. Pratama, Universitas Islam Indonesia, Jl.Kaliurang Km 14.5, Sleman DIY 55584, Indonesia
Email: ahmad.raffie@uii.ac.id

1. INTRODUCTION

Indonesian authorities declared in March 2020 that the COVID-19 pandemic had officially entered the country. As a result, various risk-mitigation policies have been implemented since then. Among them was a policy promoting learning at home that is applicable to all levels of education nationwide. Several researchers have examined how Indonesians, particularly parents of school-aged children, respond to this learning from home policy [1]–[3]. However, the majority, if not all, of them rely on online surveys with relatively small sample sizes, limiting their generalizability. On the other hand, the availability of big data and one's digital footprint on social media enables the conduct of nationwide sentiment analysis with significantly less effort than traditional survey methods. Another advantage of using digital footprints over survey methods is that they capture something that has already happened rather than one's opinions of what could happen or has happened. This is also why digital footprints on the internet in general, and social media in particular, have been extensively used to investigate a variety of sensitive social issues, including but not limited to vaccinations [4].

hate speech [5], political preferences [6], climate change [7], domestic violence [8], pop culture [9], cybersecurity and privacy [10], online donations [11], and online fraud [12].

There are numerous studies in the literature that analyze the sentiment of social media posts using a variety of text-based analysis methods, ranging from linguistic and semantic approaches such as knowledge mining [13] and lexicon [14]–[16] to computational approaches such as machine learning [17]–[19] and deep learning [20]–[22]. While each of these text-based sentiment analysis methods has distinct advantages and disadvantages, they all require considerable effort to accomplish the goal. On the other hand, since 2016, Facebook has offered a variety of reactions (e.g., like, love, wow, haha, sad, angry, and care) that can be used in place of text-based methods for sentiment analysis. In recent years, researchers in a number of countries, including Austria [23], [24], Brazil [25], Germany [26], Mexico [27], The Netherlands [28], Tunisia [29], United Kingdom [30], [31], and United States [32]–[34] have started to employ them as an alternative to the text-based sentiment analysis in a wide range of social issues.

Unfortunately, this is not the case in Indonesia, where more research on sentiment analysis on social media is concentrated on text-based sentiment analysis and on different platforms, such as Twitter [35]–[39] and Instagram [40]–[43], instead. Given that the number of Facebook users in Indonesia will be close to 130 million by 2022, which is still greater than even the combination of Twitter users (18 million) and Instagram users (99 million) in Indonesia [44], a sentiment analysis conducted on Facebook may have a more direct impact on real-life than a sentiment analysis on the same issue conducted on Twitter or Instagram. This research aims to close that gap in the literature by pioneering the use of Facebook reactions as an alternative to text-based sentiment analysis on social media, with a special emphasis on the Indonesian context and social issues. Additionally, it demonstrates how Facebook's special reactions can be combined with text-based sentiment analysis to paint a complete picture of the social issue under investigation. This research, in particular, examines the topic of learning from home during the COVID-19 pandemic, which is not only timely but also relatable to almost everyone in the country, as it may affect them directly or indirectly through someone close to them.

2. METHOD

Fig. 1 depicts the research method employed in this study, which consists of three major steps that are discussed in more detail in the following subsections.

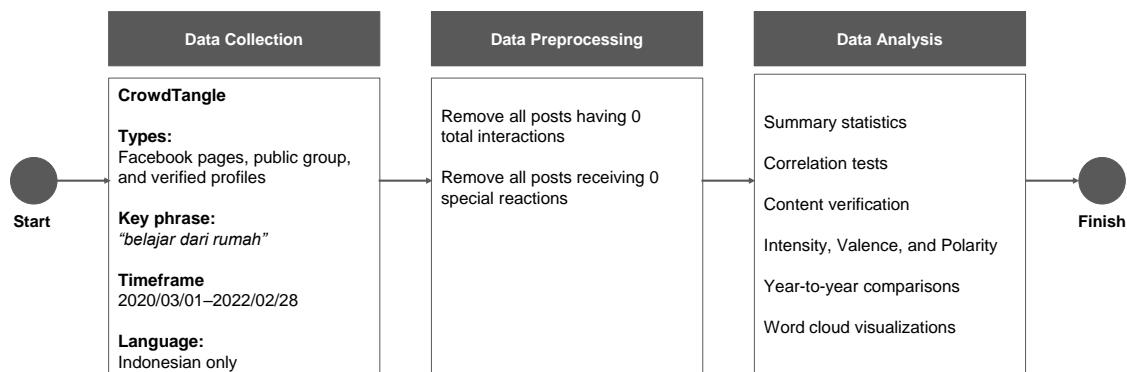


Fig. 1. Research method

2.1. Data collection

CrowdTangle [45], a tool owned by Meta, the parent company of Facebook, that tracks interactions on public content from Facebook pages, groups, and verified profiles, was used to collect the dataset for this study. The dataset was compiled using the key phrase "belajar dari rumah" with double quotes to obtain only direct matches, in addition to several filters, including the following: 1) any account type (pages, public group, or verified profile), 2) posted in the Indonesian language, and 3) timeframe between March 1, 2020, and February 28, 2022. The default settings for all other filters were retained, as shown in Fig. 2. This process resulted in a total of 39,657 posts. The raw dataset in CSV format is made publicly accessible at <https://s.id/bdrfbposts>.

2.2. Data preprocessing

The following step is to preprocess and clean the data prior to analysis, as illustrated in the middle part of Fig. 1. Upon initial inspection, it appears that a significant number of posts received no interaction at all and thus had to be excluded from the dataset. Following that, of the seven click-based reactions available on

Facebook (like, love, wow, haha, sad, angry, and care), the like button is considered the default, while the other six are considered special reactions. Numerous studies have demonstrated that the “like” button consistently outnumbers the other six special reactions and that people use it for more than just indicating their liking for a post. Thus, the number of likes a post receives on Facebook is not a good indicator of its valence [33], [46]. As a result, only special reactions will be used to determine sentiment in this study, which means that all posts receiving no special reactions will be excluded from the dataset. After this preprocessing step was completed, 9,310 posts remained to be quantitatively analyzed.

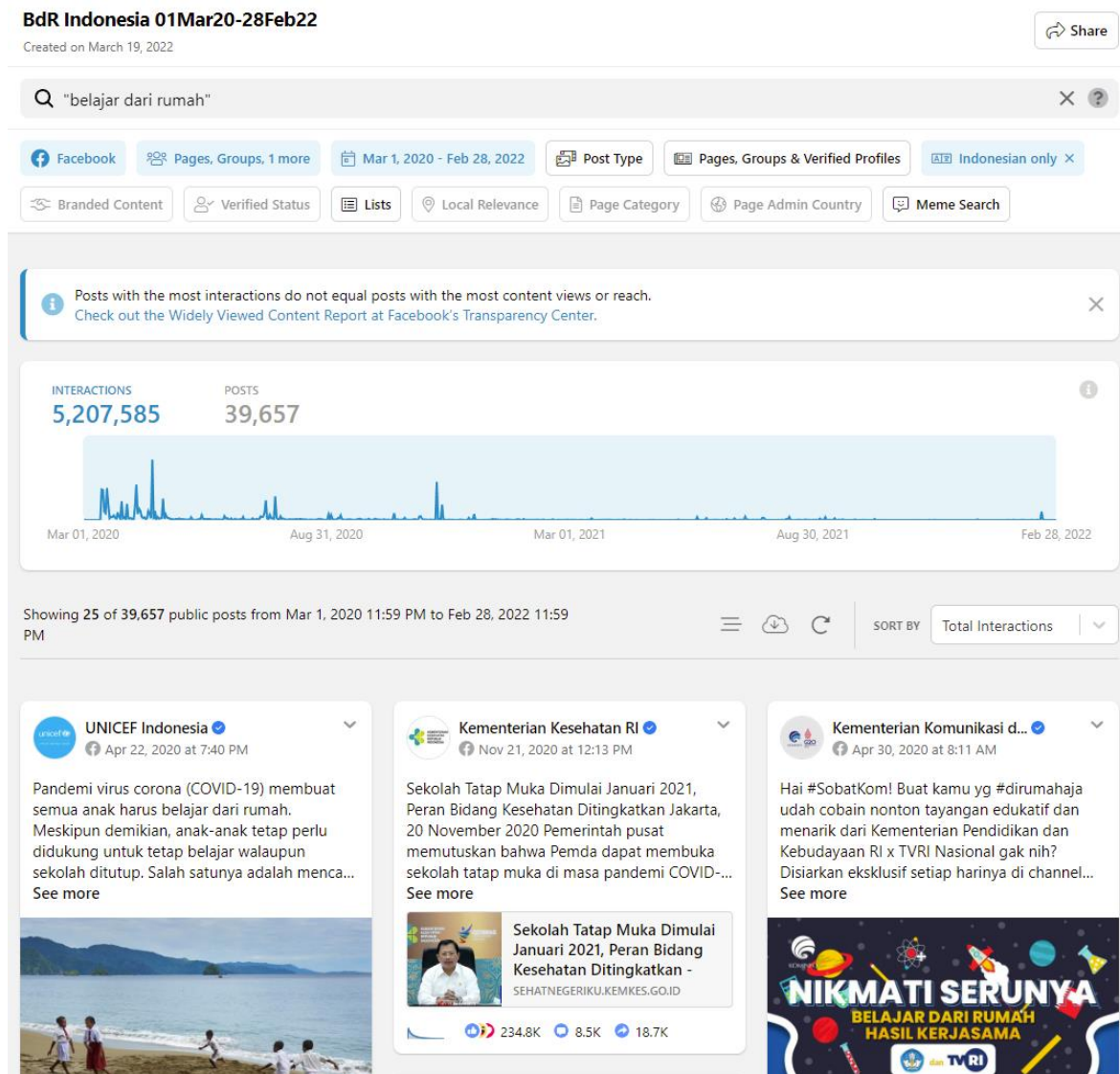


Fig. 2. Data collection through CrowdTangle

2.3. Data analysis

The first part of the analysis was done by creating some new calculated variables in the dataset, as summarized in Table 1. These new variables were meant to indicate a) what special reactions are received by each post, b) the proportion of each special reaction received by each post, c) the intensity of special reactions received by each post, d) the valence of each post, and e) the polarity score of each post.

Other research on Facebook special reactions in the United States found that only “sad” and “angry” are classified as special negative reactions, while “haha” and “wow” are classified as neutral or undecided [33], [34]. However, it may not be directly applicable to this research due to the cultural differences between the two countries and the research’s exclusion of “care” reactions. As a result, a series of correlation analyses will be

conducted between all the special reactions in this dataset to determine the most appropriate membership for special reactions with negative valence.

Table 1. New calculated variables

Name	Description	Formula
hasSR [±]	The post contains this particular special reaction	If the post receives no SR [±] then hasSR [±] = 0, else hasSR = 1
pSR [±]	The proportion of this particular special reaction of all special reactions received by post	$\sum \text{SR}^{\pm} / \sum \text{All SR}$
Intensity	The proportion of all special reactions overall click-based reactions received by post	$\sum \text{All SR} / \sum \text{All click-based reactions}$
Valence	The positive or negative valence of the post	If the post receives less $\sum \text{SR}^+$ than $\sum \text{SR}^-$ then valence = -1, else valence = 1
Polarity	The magnitude of positive or negative sentiment received by post	Intensity \times Valence








Note: SR[±] applicable for each of the special reactions (i.e., love, wow, haha, sad, angry, and care);
SR⁺ applicable for all special reactions with positive valence (to be determined)
SR⁻ applicable for all special reactions with negative valence (to be determined)

The following analysis will divide the dataset into two categories based on the date the post was created: posts created during the first year of COVID-19 (i.e., March 2020 to February 2021) and posts created during the second year of COVID-19 (i.e., March 2021 to February 2022). A few comparisons of the number of posts, their valence, and their polarity will be made to determine whether there is any discernible pattern in the dataset. Finally, word cloud visualizations will be used to gain meaningful insight into the dataset's content with varying degrees of the sentiment of the learning from the home topic in Indonesia during the COVID-19 pandemic. All analyses were conducted on Google Colab using Python 3.6.9. The complete source code is available for public access on GitHub at <https://github.com/ahmadrafie/bdrfbposts>.

3. RESULTS AND DISCUSSION

Table 2 shows the summary statistics for all click-based reactions received by all posts in the dataset. As can be seen, the “like” button outnumbers all special reactions combined by far, confirming further that the exclusion of this button from further analysis as what other researchers did is fully justified.

Table 2. Summary statistics of all click-based reactions

Reaction	Statistics						
	Mean	Std. Dev	Min	25%	50%	75%	Max
 Like	396.92	5,743.20	0	8.00	31.00	101.00	404,277.00
 Love	14.37	261.27	0	0	1.00	3.00	15,366.00
 Wow	1.47	32.54	0	0	0	0	2,938.00
 Haha	4.42	61.98	0	0	0	0	3,267.00
 Sad	2.49	37.17	0	0	0	0	2,849.00
 Angry	0.54	3.82	0	0	0	0	204.00
 Care	0.91	12.77	0	0	0	0	706.00

Following that, the results of a series of correlation analyses between all special reactions in the dataset are shown in Fig. 3 for the mean distribution of each special reaction and in Fig. 4 for the proportion of all posts receiving each special reaction. As illustrated in the two figures, the “love” reaction stands out in comparison to all other special reactions. While the distribution of the “love” reaction is moderately correlated with that of the “care” reaction, its proportion is either negative or extremely weakly correlated with the other reactions, including “care.” According to the correlations (> 0.200) between the proportion of all posts receiving each special reaction, as shown in Fig. 4, the most frequently received pairs by the same post are “haha” and “angry” at 0.366, “wow” and “haha” at 0.352, “wow” and “angry” at 0.348, “angry” and “care” at 0.295, and “wow” and “sad.” Further manual examination of the posts' actual content reveals that these combinations appear to represent mockery, anger, disgust, sadness, or condolences, all of which have a negative

valence in comparison to the pleasure and joy represented by the “love” reaction. As a result, all five special reactions except “love” are classified as special reactions with a negative valence in this study.

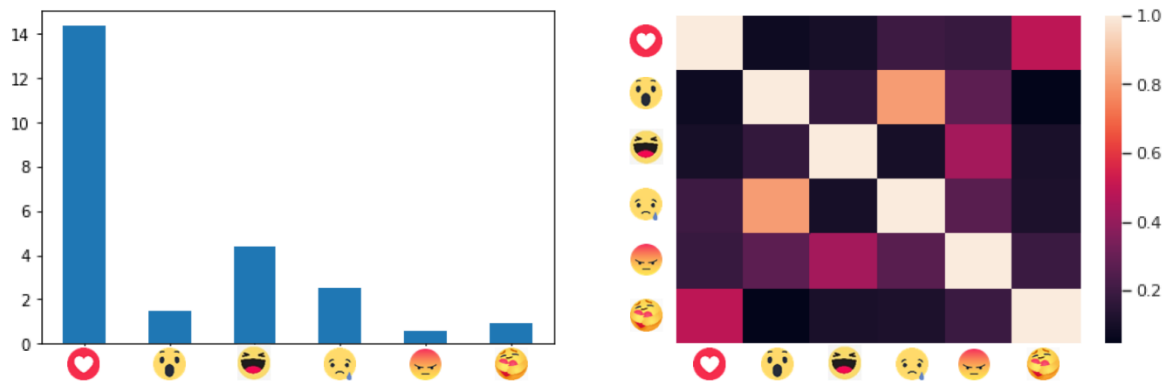


Fig. 3. The distribution of means for each special reaction (left) and the correlation heatmap (right)

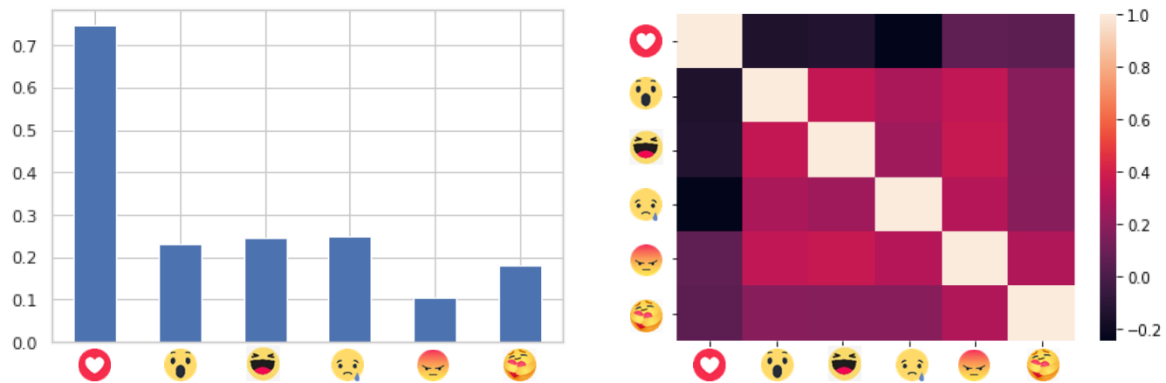


Fig. 4. The proportion of all posts receiving each special reaction (left) and the correlation heatmap (right)

Based on the membership assignment of each special reaction in the preceding step, the values for the three variables used to quantify the sentiment expressed in each Facebook post in the dataset, namely intensity, valence, and polarity, were calculated, as summarized in Table 3. The positive value of the mean in valence indicates that there are more positive valence posts than negative valence posts in the dataset. The negative value of the mean in polarity, on the other hand, indicates that there are more posts with a negative valence having a greater intensity (i.e., receiving more special reactions in proportion to all click-based reactions) than those with a positive valence.

Table 3. Summary statistics of intensity, valence, and polarity from all posts in the dataset

Variable	Statistics						
	Mean	Std. Dev	Min	25%	50%	75%	Max
Intensity	0.197	0.266	0.001	0.037	0.091	0.223	1.000
Valence	0.286	0.958	-1.000	-1.000	1.000	1.000	1.000
Polarity	-0.018	0.331	-1.000	-0.056	0.030	0.111	1.000

As summarized in Table 4, the first year of the COVID-19 pandemic saw significantly more posts receiving special reactions than the second year. Additionally, there were significantly more positive than negative valence posts in the first year but no difference in the second year, as confirmed by the chi-square test $\chi^2(1, N = 9,310) = 5.36, p = .0021$. The density plot in Fig. 5 demonstrates the stark contrast between posts in the first and second years of the COVID-19 pandemic. One of the most plausible explanations is that by the second year of the pandemic, more people had grown tired of both the pandemic and the learning from home policy. As a result, fewer posts about learning from home received special reactions in total, though many of those that did receive reactions received more negative responses than if they were posted in the first year of the pandemic.

Table 4. Post valence categorized by year

Valence	First Year		Second Year	
	N	Percentage	N	Percentage
Positive	5,192	67.21%	794	50.09%
Negative	2,533	32.79%	791	49.91%

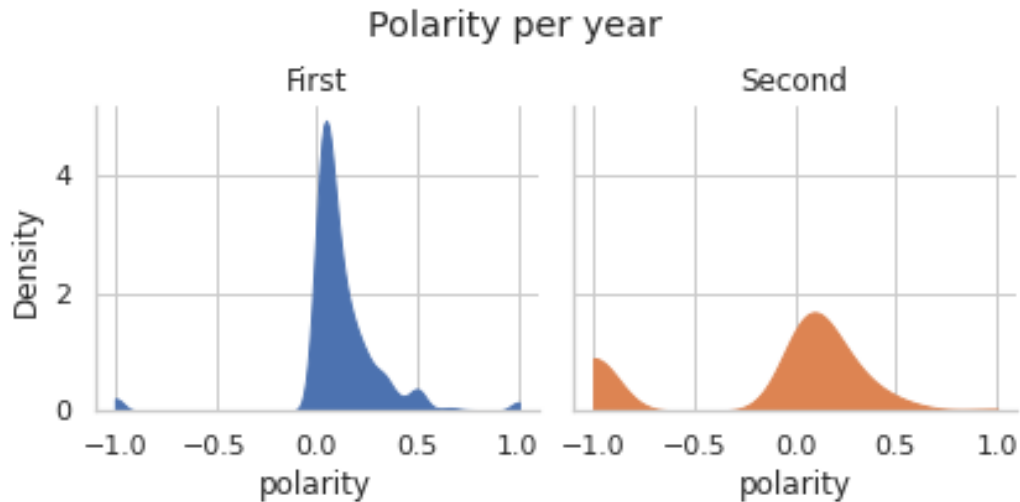


Fig. 5. Some examples of posts with high polarity (top) and low polarity (bottom)

To provide a better understanding of each post’s content, Fig. 6 depicts several of these posts with varying degrees of polarity. A cursory examination of the messages in the posts reveals a significant difference in the wording used in posts in two different categories. Positive polarity posts contain normative and optimistic messages, whereas negative polarity posts frequently contain bombastic and clickbait language. Additionally, when it comes to posts with a high negative polarity value, there is an indication of political preferences at work in some cases.

polarity	intensity	Message	pLove	pHaha	pWow	pSad	pAngry	pCare	
3	0.125	0.125	Kami sudah menjalani tes deteksi Covid-19. Alh...	0.971	0.017	0.007	0.004	0.001	0.000
7	0.122	0.122	Terima kasih dan penghargaan yang setinggi-tin...	0.960	0.006	0.004	0.030	0.001	0.000
6	0.101	0.101	Pernah ada masa di negeri ini guru mengajar di...	0.929	0.007	0.002	0.003	0.001	0.058
10	0.142	0.142	Anak-anakku di seluruh Tanah Air, apa kabar se...	0.899	0.014	0.004	0.005	0.001	0.077
4	0.080	0.080	Hari Lebaran masih dua bulan lagi, tapi rupany...	0.846	0.032	0.014	0.103	0.005	0.000
polarity	intensity	Message	pLove	pHaha	pWow	pSad	pAngry	pCare	
14000	-1.0	1.0	Jokowi wajib turun....	0.0	1.0	0.0	0.0	0.0	0.0
17568	-1.0	1.0	Belajar dari Rumah, KPAI: Ada 51 Aduan Keluhka...	0.0	1.0	0.0	0.0	0.0	0.0
18564	-1.0	1.0	Gara* Bekerja dari Rumah & Belajar dari Rumah...	0.0	1.0	0.0	0.0	0.0	0.0
21469	-1.0	1.0	*Konferensi Pers Gubernur DKI Jakarta, 9 Septe...	0.0	1.0	0.0	0.0	0.0	0.0
21635	-1.0	1.0	Sesuatu dimulai dari pembuatan tugas sekolah b...	0.0	0.0	1.0	0.0	0.0	0.0

Fig. 6. Some examples of posts with high polarity (top) and low polarity (bottom)

Finally, the word cloud visualizations in Fig. 7 reveal another intriguing finding of the content of posts with a positive and, more importantly, a negative valence. As it turns out, the words “internet” and “unlimited” are quite prevalent in posts with a negative valence but are almost nonexistent in posts with a positive valence. A straightforward explanation for this phenomenon is that some people are experiencing significant difficulties with their IT infrastructure, which is ostensibly impeding their learning from home activities.



Fig. 7. Word cloud visualization of message in posts with positive (left) and negative (right) valence

4. CONCLUSION

While in Indonesia, sentiment analysis research is mostly focused on text-based sentiment analysis on Twitter and Instagram, researchers from all over the world are increasingly interested in using Facebook's special reactions for their research. When combined with CrowdTangle, which enables researchers to easily collect public data from Facebook, this approach can be a powerful tool for conducting rapid sentiment analysis. This study demonstrated how to conduct sentiment analysis on special reactions on Facebook, particularly with an emphasis on the Indonesian context, which is still limited in the literature. Nonetheless, this study only scratches the surface of what researchers can accomplish with Facebook's special reactions. There is much more that can be done if more researchers are willing to investigate these topics in greater detail. For instance, additional analysis can be conducted across page categories to determine whether there are discrepancies in public sentiment regarding posts made by various types of Facebook pages and verified profiles or in various categories of Facebook public groups. A cross-country comparison is another option, particularly given that the special reactions indicating negative valence in this study from Indonesia are distinct from those used by other researchers using data from the United States. In summary, this approach has significant potential for analyzing contemporary social issues using big data and digital footprints on social media. Researchers can also use this reaction-based method in conjunction with text-based sentiment analysis to get a better sense of the social issue at hand and make a better model in machine learning or deep learning.

Acknowledgments

The author would like to thank the Department of Informatics, Universitas Islam Indonesia, for providing a publication grant to cover the publication fee for this article.

REFERENCES

- [1] A. R. Pratama and F. M. Firmansyah, "Disengaged, Positive, or Negative: Parents' Attitudes Toward Learning From Home Amid COVID-19 Pandemic," *Journal of Child and Family Studies*, vol. 30, no. 7, pp. 1803–1812, May 2021, <https://doi.org/10.1007/s10826-021-01982-8>.
- [2] E. Susilowati and M. Azzasyofia, "The parents stress level in facing children study from home in the early of COVID-19 pandemic in Indonesia," *International Journal of Science and Society*, vol. 2, no. 3, pp. 1–12, Jul. 2020, <https://doi.org/10.54783/ijssoc.v2i3.117>.
- [3] D. Lase, T. G. C. Zega, and D. O. Daeli, "Parents' perceptions of distance learning during COVID-19 pandemic in rural Indonesia," *SSRN Electron. J.*, 2021, <https://doi.org/10.2139/ssrn.3890610>.
- [4] H. Piedrahita-Valdés, D. Piedrahita-Castillo, J. Bermejo-Higuera, P. Guillem-Saiz, J. R. Bermejo-Higuera, J. Guillem-Saiz, J. A. Sicilia-Montalvo, and F. Machío-Regidor, "Vaccine hesitancy on social media: Sentiment analysis from June 2011 to April 2019," *Vaccines (Basel)*, vol. 9, no. 1, p. 28, Jan. 2021, <https://doi.org/10.3390/vaccines9010028>.
- [5] L. Jiang and Y. Suzuki, "Detecting hate speech from tweets for sentiment analysis," *2019 6th International Conference on Systems and Informatics (ICSAI)*, 2019, <https://doi.org/10.1109/ICSAI48974.2019.9010578>.

- [6] D. J. S. Oliveira, P. H. de S. Bermejo, and P. A. dos Santos, "Can social media reveal the preferences of voters? A comparison between sentiment analysis and traditional opinion polls," *J. inf. technol. politics*, vol. 14, no. 1, pp. 34–45, Jan. 2017, <https://doi.org/10.1080/19331681.2016.1214094>.
- [7] B. Dahal, S. A. P. Kumar, and Z. Li, "Topic modeling and sentiment analysis of global climate change tweets," *Soc. Netw. Anal. Min.*, vol. 9, no. 1, Dec. 2019, <https://doi.org/10.1007/s13278-019-0568-8>.
- [8] K. More and F. Francis, "Analyzing the impact of domestic violence on social media using natural language processing," *2021 IEEE Pune Section International Conference (PuneCon)*, 2021, <https://doi.org/10.1109/PuneCon52575.2021.9686490>.
- [9] F. M. Firmansyah and J. J. Jones, "Did the black panther movie make blacks blacker? Examining black racial identity on twitter before and after the black panther movie release," *Lecture Notes in Computer Science*, Cham: Springer International Publishing, 2019, pp. 66–78, https://doi.org/10.1007/978-3-030-34971-4_5.
- [10] A. Sriram, Y. Li, and A. Hadaegh, "Mining social media to understand user opinions on IoT security and privacy," *2021 IEEE International Conference on Smart Computing (SMARTCOMP)*, 2021, <https://doi.org/10.1109/SMARTCOMP52413.2021.00056>.
- [11] F. M. Firmansyah and A. R. Pratama, "Anonymity in COVID-19 online donations: A cross-cultural analysis on fundraising platforms," *Advances in Intelligent Systems and Computing*, Cham: Springer International Publishing, 2021, pp. 34–47, https://doi.org/10.1007/978-3-030-73103-8_3.
- [12] E. Kauffmann, J. Peral, D. Gil, A. Ferrández, R. Sellers, and H. Mora, "A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake review detection for marketing decision-making," *Ind. Mark. Manag.*, Aug. 2019, <https://doi.org/10.1016/j.indmarman.2019.08.003>.
- [13] F. Neri, C. Aliprandi, F. Capeci, M. Cuadros, and T. By, "Sentiment Analysis on Social Media," *2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012)*, 2012, <https://doi.org/10.1109/ASONAM.2012.164>.
- [14] A. Baj-Rogowska, "Sentiment analysis of Facebook posts: The Uber case," *2017 Eighth International Conference on Intelligent Computing and Information Systems (ICICIS)*, 2017, <https://doi.org/10.1109/INTELCIS.2017.8260068>.
- [15] S. Akter and M. T. Aziz, "Sentiment analysis on facebook group using lexicon based approach," *2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)*, 2016, <https://doi.org/10.1109/CEEICT.2016.7873080>.
- [16] K. M. Nahar, A. Jaradat, M. S. Atoum, and F. Ibrahim, "Sentiment analysis and classification of arab jordanian facebook comments for jordanian telecom companies using lexicon-based approach and machine learning," *Jordanian Journal of Computers and Information Technology (JJCIT)*, vol. 6, no. 03, pp. 52–71, 2020, <https://doi.org/10.5455/jjcit.71-1586289399>.
- [17] K. Zahoor, N. Z. Bawany, and S. Hamid, "Sentiment analysis and classification of restaurant reviews using machine learning," *2020 21st International Arab Conference on Information Technology (ACIT)*, 2020, <https://doi.org/10.1109/ACIT50332.2020.9300098>.
- [18] M. Meire, M. Ballings, and D. Van den Poel, "The added value of auxiliary data in sentiment analysis of Facebook posts," *Decis. Support Syst.*, vol. 89, pp. 98–112, Sep. 2016, <https://doi.org/10.1016/j.dss.2016.06.013>.
- [19] M. T. Hoque, A. Islam, E. Ahmed, K. A. Mamun, and M. N. Huda, "Analyzing performance of different machine learning approaches with Doc2vec for classifying sentiment of Bengali natural language," *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 2019, <https://doi.org/10.1109/ECACE.2019.8679272>.
- [20] S. Subramani, H. Wang, H. Q. Vu, and G. Li, "Domestic violence crisis identification from Facebook posts based on deep learning," *IEEE Access*, vol. 6, pp. 54075–54085, 2018, <https://doi.org/10.1109/ACCESS.2018.2871446>.
- [21] L.-C. Cheng and S.-L. Tsai, "Deep learning for automated sentiment analysis of social media," *ASONAM '19: International Conference on Advances in Social Networks Analysis and Mining*, 2019, <https://doi.org/10.1145/3341161.3344821>.
- [22] Z. Kastrati, L. Ahmedi, A. Kurti, F. Kadriu, D. Murtezaj, and F. Gashi, "A deep learning sentiment analyser for social media comments in low-resource languages," *Electronics (Basel)*, vol. 10, no. 10, p. 1133, May 2021, <https://doi.org/10.3390/electronics10101133>.
- [23] J.-M. Eberl, P. Tolochko, P. Jost, T. Heidenreich, and H. G. Boomgaarden, "What's in a post? How sentiment and issue salience affect users' emotional reactions on Facebook," *Journal of Information Technology & Politics*, vol. 17, no. 1, pp. 48–65, Jan. 2020, <https://doi.org/10.1080/19331681.2019.1710318>.
- [24] F. Poecze, C. Ebster, and C. Strauss, "Social media metrics and sentiment analysis to evaluate the effectiveness of social media posts," *Procedia Comput. Sci.*, vol. 130, pp. 660–666, 2018, <https://doi.org/10.1016/j.procs.2018.04.117>.
- [25] F. T. Giuntini, L. P. Ruiz, L. D. F. Kirchner, D. A. Passarelli, M. D. J. D. Dos Reis, A. T. Campbell, and J. Ueyama, "How Do I Feel? Identifying Emotional Expressions on Facebook Reactions Using Clustering Mechanism," *IEEE Access*, vol. 7, pp. 53909–53921, undefined 2019, <https://doi.org/10.1109/ACCESS.2019.2913136>.
- [26] B. T. Raad, B. Philipp, H. Patrick, and M. Christoph, "ASEDS: Towards Automatic Social Emotion Detection System Using Facebook Reactions," *2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data*

- Science and Systems (HPCC/SmartCity/DSS)*, 2018, pp. 860–866, <https://doi.org/10.1109/HPCC/SmartCity/DSS.2018.00143>.
- [27] R. Sandoval-Almazan and D. Valle-Cruz, “Sentiment Analysis of Facebook Users Reacting to Political Campaign Posts,” *Digit. Gov.: Res. Pract.*, vol. 1, no. 2, pp. 1–13, Apr. 2020, <https://doi.org/10.1145/3382735>.
- [28] T. Moers, F. Krebs, and G. Spanakis, “SEMtec: Social emotion mining techniques for analysis and prediction of Facebook post reactions,” *Lecture Notes in Computer Science*, 2019, pp. 361–382, https://doi.org/10.1007/978-3-030-05453-3_17.
- [29] O. Oueslati, A. I. S. Khalil, and H. Ounelli, “Sentiment analysis for helpful reviews prediction,” *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 7, no. 3, pp. 34–40, Jun. 2018, <https://doi.org/10.30534/ijatcse/2018/02732018>.
- [30] Y. Tian, T. Galery, G. Dulcinati, E. Molimpakis, and C. Sun, “Facebook sentiment: Reactions and Emojis,” *Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media*, 2017, <https://doi.org/10.18653/v1/W17-1102>.
- [31] S. Turnbull and S. Jenkins, “Why Facebook Reactions are good news for evaluating social media campaigns,” *Journal of Direct, Data and Digital Marketing Practice*, vol. 17, no. 3, pp. 156–158, Feb. 2016, <https://doi.org/10.1057/ddmp.2015.56>.
- [32] T. Tran, D. Nguyen, A. Nguyen, and E. Golen, “Sentiment analysis of marijuana content via Facebook emoji-based reactions,” *2018 IEEE International Conference on Communications (ICC 2018)*, 2018, <https://doi.org/10.1109/ICC.2018.8422104>.
- [33] C. Freeman, H. Alhoori, and M. Shahzad, “Measuring the Diversity of Facebook Reactions to Research,” *Proc. ACM Hum.-Comput. Interact.*, vol. 4, no. GROUP, pp. 1–17, Jan. 2020, <https://doi.org/10.1145/3375192>.
- [34] C. Freeman, M. K. Roy, M. Fattoruso, and H. Alhoori, “Shared feelings: Understanding Facebook reactions to scholarly articles,” *2019 ACM/IEEE Joint Conference on Digital Libraries (JCDL)*, 2019, <https://doi.org/10.1109/JCDL.2019.00050>.
- [35] V. A. Fitri, R. Andreswari, and M. A. Hasibuan, “Sentiment analysis of social media twitter with case of anti-LGBT campaign in Indonesia using naïve Bayes, decision tree, and random forest algorithm,” *Procedia Comput. Sci.*, vol. 161, pp. 765–772, 2019, <https://doi.org/10.1016/j.procs.2019.11.181>.
- [36] E. Miranda, M. Aryuni, R. Hariyanto, and E. S. Surya, “Sentiment Analysis using Sentiwordnet and Machine Learning Approach (Indonesia general election opinion from the twitter content),” *2019 International Conference on Information Management and Technology (ICIMTech)*, 2019, pp. 62–67, <https://doi.org/10.1109/ICIMTech.2019.8843734>.
- [37] S. H. Sahir, R. S. Ayu Ramadhana, M. F. Romadhon Marpaung, S. R. Munthe, and R. Watrionthos, “Online learning sentiment analysis during the covid-19 Indonesia pandemic using twitter data,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 1156, no. 1, p. 012011, Jun. 2021, <https://doi.org/10.1088/1757-899X/1156/1/012011>.
- [38] W. Budiharto and M. Meiliana, “Prediction and analysis of Indonesia Presidential election from Twitter using sentiment analysis,” *J. Big Data*, vol. 5, no. 1, Dec. 2018, <https://doi.org/10.1186/s40537-018-0164-1>.
- [39] I. P. Windasari, F. N. Uzzi, and K. I. Satoto, “Sentiment analysis on Twitter posts: An analysis of positive or negative opinion on GoJek,” *2017 4th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*, 2017, <https://doi.org/10.1109/ICITACEE.2017.8257715>.
- [40] H. Sudira, A. L. Diar, and Y. Ruldeviyani, “Instagram sentiment analysis with naïve Bayes and KNN: Exploring customer satisfaction of digital payment services in Indonesia,” *2019 International Workshop on Big Data and Information Security (IWBIS)*, 2019, <https://doi.org/10.1109/IWBIS.2019.8935700>.
- [41] D. T. Alamanda, A. Ramdhani, I. Kania, W. Susilawati, and E. S. Hadi, “Sentiment analysis using text mining of Indonesia tourism reviews via social media,” *Int. J. Humanit. Arts Soc. Sci.*, vol. 5, no. 2, pp. 72–82, Apr. 2019, <https://doi.org/10.20469/ijhss.5.10004-2>.
- [42] M. Z. Naf’an, A. A. Bimantara, A. Larasati, E. M. Risondang, and N. A. S. Nugraha, “Sentiment analysis of cyberbullying on Instagram user comments,” *J. Data Sci. Appl.*, vol. 2, no. 1, pp. 88–98, Apr. 2019, <https://doi.org/10.21108/jdsa.2019.2.20>.
- [43] M. Rosanensi, M. Madani, R. T. P. Wanggono, A. Setyanto, A. A. Selameto, and S. N. Wahyuni, “Analysis sentiment and tourist response to rinjani mountain tour based on comments from photo upload in Instagram,” *2018 3rd International Conference on Information Technology, Information System and Electrical Engineering (ICITISEE)*, 2018, <https://doi.org/10.1109/ICITISEE.2018.8720960>.
- [44] S. Kemp, “Digital 2022: Indonesia,” *DataReportal – Global Digital Insights*, Feb. 15, 2022, <https://datareportal.com/reports/digital-2022-indonesia> (accessed Mar. 19, 2022).
- [45] CrowdTangle Team, “CrowdTangle,” *CrowdTangle*, 2019, <https://crowdtangle.com/> (accessed Mar. 10, 2022).
- [46] T. Vepsäläinen, H. Li, and R. Suomi, “Facebook likes and public opinion: Predicting the 2015 Finnish parliamentary elections,” *Gov. Inf. Q.*, vol. 34, no. 3, pp. 524–532, Sep. 2017, <https://doi.org/10.1016/j.giq.2017.05.004>.

BIOGRAPHY OF AUTHORS

Ahmad R. Pratama is an Assistant Professor at Universitas Islam Indonesia, currently serving as the Secretary of the Department of Informatics. He did his Ph.D. in Technology, Policy, and Innovation at Stony Brook University with a Fulbright scholarship while also participating in the Inter-University Doctoral Consortium at New York University and Teachers College, Columbia University. Previously, he earned his Master's degree in Information Technology from Monash University and his Bachelor of Engineering degree from Universitas Gadjah Mada. His research interests are mainly related to technology and society in various domains, such as education, e-commerce, security, and forensics, as well as apps and social media.