ELite Journal : International Journal of Education, Language, and Literature
Volume 2 (3) 2022
ISSN: 2621-8127 (online)
https://journal.unesa.ac.id/index.php/elite

Spread of Toxic Speech Trough Pejorative Words on Twitter during Coronavirus Outbreak

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ABSTRACT

This research aims to convince the existence of toxic speech on social media, especially on Twitter, and its effect on the internet citizen mindset that can construct new culture on how people use language on Twitter during the coronavirus outbreak. The research problems of this study are the kind of toxic speech frequently used on Twitter, how toxic speech containing pejorative words spreads, and how it shapes Twitter cyberculture. This study utilized Tirrell and Ralston's toxic-speech theory to define and classify the tweet. This study used qualitative research with non-participant observation and documentation as the data collection technique. The data obtained were a tweet about coronavirus from influential people containing the pejorative word. Then, the data were classified based on the toxicity level of the tweet that meets the toxic speech classification criteria combined with speech act theory and the LIWC program. The first analysis revealed the existence of toxic speech on Twitter and the type of toxic speech frequently found on Twitter. After classifying, ICM transmitted the whole tweet's meaning by recognizing the pejorative words. This study found that toxic speech spreads on Twitter with the ratio of 2:1 for discursive morbidity is frequently found on Twitter. It also can shape the new culture on Twitter seen from the netizen response.

Keywords: Toxic speech, pejorative words, Twitter, cyberculture, coronavirus

ABSTRAK

Penelitian ini bertujuan untuk meyakinkan keberadaan *toxic speech* di media sosial, khususnya Twitter, dan pengaruhnya terhadap pola pikir warga internet yang dapat mengkonstruksi budaya baru tentang bagaimana orang menggunakan bahasa di Twitter selama wabah virus corona. Rumusan masalah dari studi ini adalah jenis *toxic speech* yang sering digunakan di Twitter, bagaimana *toxic speech* yang mengandung kata-kata merendahkan menyebar, dan bagaimana hal itu membentuk budaya siber Twitter. Penelitian ini menggunakan teori Tirrell dan Ralston tentang *toxic speech* untuk mendefinisikan dan mengklasifikasikan tweet. Penelitian ini menggunakan penelitian kualitatif dengan observasi non partisipan dan dokumentasi sebagai teknik pengumpulan data. Data tersebut diperoleh dari tweet tentang virus corona dari orang-orang berpengaruh yang mengandung kata merendahkan. Kemudian, data tersebut diklasifikasikan berdasarkan tingkat toksisitas tweet yang memenuhi kriteria klasifikasi ucapan beracun yang digabungkan dengan teori tindak tutur dan program LIWC. Analisis pertama mengungkapkan adanya *toxic speech* di Twitter dan jenis *toxic speech* yang sering ditemukan di Twitter. Setelah mengklasifikasi, ICM mentransmisikan seluruh makna tweet dengan mengenali kata-kata yang merendahkan.

Penelitian ini menemukan bahwa *toxic speech* menyebar di Twitter dengan rasio 2:1 untuk morbiditas diskursif sebagai jenis yang sering ditemukan di Twitter. Hal ini juga dapat membentuk budaya baru di Twitter dilihat dari respon warga internet.

Kata kunci: *Toxic speech*, kata-kata merendahkan, Twitter, budaya siber, coronavirus

INTRODUCTION

After WHO declared the coronavirus outbreak as a pandemic, it caused mass panic for the citizen and the government since most of them are not ready yet to face this outbreak, which happens in most countries worldwide. This condition is also appalling to people on social media, especially Twitter. Based on the observation, this outbreak affects Twitter users since Twitter is one of the frequent social media to get and share information. Information updates regarding the pandemic on Twitter also spread quickly since the government and several related organizations also use Twitter to share the newest update about the pandemic.

Twitter monitored approximately 303 million people tweeting related to Covid-19, 222,774 mentioning WHO crises, almost 21% noting about Covid-19, and the government failed to handle it (Burkle et al., 2020). This situation is quite dangerous because the citizen will fall into the wrong information. Then, they spread this information, and it all ends up with mass panic due to their quandary of much information they have received. While there is a new dangerous term that threatens twitter-users named toxic speech, and unfortunately, Twitter does not have a detector to prevent the user from the danger of toxic speech.

Toxic speech is a study about harmful speech that can marginalize a group of people when brought into the public sphere (Tirrell, 2017). This study focuses on toxic speech, which threatens the well-being and lives of those against whom the toxic speech deploys it. It is a community problem in need of social solutions and much broader than stigma and derogation. It can also make sense of claims about harms arising from speech devoid of slurs, epithets, or narrow class or called deeply derogatory terms. Based on Tirrell’s theory, there are two types of toxic speech. The first is discursive mortality which is the degree of discourse that has the power to change the view or even kill its users, targets, and bystanders. Discursive mortality uses language as a deadly weapon in spreading harmful discourse. The second is discursive morbidity which is the degree of discourse that is unhealthy for the user. For an individual, this toxic speech type might result from a single dose with a long latency period, for instance, speech criticizing someone ‘under the skin’ or, in short, its metaphor of indirect challenge just like a sexist joke on women and their politic position. This research analyzes toxic speech using Tirrell’s theory about toxic speech with several supporting approaches to make this study reliable.

Another researcher supports the toxic speech concept using a different approach (Ralston, 2018). She mostly wanted to verify Tirrell’s research about toxic speech through linguistic aspects by combining her toxic speech theory with speech act and metaphorical approach to show the toxicity level to make it more straightforward. Regrettably, Ralston found that the information about toxic speech is not demonstrated in detail since Tirrell’s journal (2017) only stated that speech can be poisonous. However, there is no further explanation about the infections, diseases, how the toxic speech spread, and who is the culprit and target of this toxic speech. Some individuals are more vulnerable to being harmed by, for instance, racist, and homophobic slurs, while others show preponderant resistance. There is no exact target of who will have a greater possibility of being poisoned and who will not. She simply categorizes the toxic speech based on its general impact with few explanations. This incompleteness becomes very mischievous when used to identify the spread of toxic speech on social media, especially Twitter. Twitter is one of the social media platforms with many users and is also the fastest platform to share some information without any validity filters (Anderson et al., 2018).

Twitter can spread everything spontaneously only by tweeting, re-tweeting, or sharing information (Keifer & Effenberger, 2014). Those simplicities make the users unable to differentiate whether the information they received was valid or not. They could not identify whether the data contained toxic or not because the information reciprocity is too fast to be checked further. Those making the toxic speech could spread massively on Twitter, and difficult to trace who is the doer and the target due to the massive amount of data recorded every minute (Kumar et al., 2013). This study compiled the metaphorical words, which are also considered pejorative words usually used by Twitter users as the hashtag, and classified them using toxic speech metaphor mapping by Ralston (2018).

To make the classification result more reliable, the Linguistic Inquiry and Word Count (LIWC) program was also used in this research. LIWC is a kind of program that was made by Pennebaker, Booth, and Francis in 2007 based on Bradac's studies (1986, 1999). It is applied to determine the emotion, cognitive process, and motives in the tweet's utterance. After the LIWC classification to define the writer inquiry, Idealised Cognitive Models (ICM) make the data more transparent by conveying the meaning of the pejorative words and revealing the whole tweet-writer intention. All those processes aimed to manifest toxic speech existence on Twitter, how it spreads toxins, and how it affects the netizen, whether the speaker or the reader.

Aside from that, Twitter users are essential in spreading toxic speech. It can fasten via their re-tweeting, sharing without collecting further information, and replying to influential people's tweets with negative comments that can cause misunderstanding or even harm people. Especially in this pandemic condition where people have inadequate activities to prevent the spread of the virus makes them more sensitive about everything. They spend most of their time opening their Twitter and then watching malicious content. This activity can increase the possibility of vulnerable people whom the toxic speech could poison since it affects people's health and their cultural behavior in using their language through social media. Due to these reasons, this study proposed to analyze and reveal the danger of toxic speech using linguistic tools to alleviate the spread of toxic speech on Twitter. The research problems of this study are the kind of toxic speech frequently used on Twitter, how toxic speech containing pejorative words spreads, and how it shapes Twitter cyberculture.

METHOD

According to Judith Baxter, qualitative research focuses on the text's meaningfulness, background, motivation, and key features (Litosseliti, 2010). That is why the descriptive qualitative method is used to analyze, convey the data meaning, and classify the data into a specific type based on the leading theory used in this research. This research data are utterances in the form of words, phrases, or sentences used by Twitter users with specific criteria: the tweet from influential people, like public figures, business leaders, government, and news portals, which gradually tweet about Covid-19. Those criteria are applied because they are the representation of netizens with power. Their tweet tends to receive much engagement from netizens seen from the number of followers, reaction, like, and re-tweet.

ISSN: 2621-8127 (online)
https://journal.unesa.ac.id/index.php/elite

Then, it also triggered netizens to respond negatively to their tweet and can mobilize people to change their mindset as well as show derogatory manners.

The data was recorded for eight months, from September 2020 until early April 2021. This study used non-participatory observation and documentation as the data collection techniques. This paper displayed four data with the most responses from netizens to prove the concept of spreading toxic speech from several accounts that meet the criteria. First, this study classified the tweet using the theories by Ralston (2018) and Tirrell (2017), which indicate the pejorative word as the first filter for categorizing the type of toxic speech. Second, the tweet that indicates a toxin was analyzed using the Linguistic Inquiry and Word Count (LIWC) program to reveal the tweet's various emotions, cognitive processes, and social concerns to convey its discursive effect. Third, this study used Idealised Cognitive Models (ICM) to analyze the exact message and pattern of the tweet. The result of categorizing the tweet and conveying the meaning proved which type of toxic speech frequently spread on Twitter and its effect on tweeter users.

FINDINGS AND DISCUSSION

As mentioned in the method section, LIWC and ICM analysis of four tweets discovered two tweets classified as discursive mortality and two classified as discursive morbidity, which was later specified using Ralston classification models.

DISCURSIVE MORTALITY

Two data in Table 2 and Table 3 are in discursive mortality, one in acute toxicity and another in chronic toxicity. The LIWC analysis on datum 1 and datum 2 from acute toxicity type was displayed in Table 2, and chronic toxicity in Table 3.

Table 1. Variable summary of the data (Jim Jordan and Dr. Lawrence Sellin tweets)

Variable Summary	Data	Average for Social Media, Twitter, Blog
Analytic	92.8	55.92
Clout	5.7	55.45
Authenticity	1.0	55.66
Emotional tone	1.0	63.35

Table 2. Datum 1: LIWC analysis result on Jim Jordan tweet

LICW Dimensions	Data	Average for Social Media, Twitter, Blog
I-words (I, Me, My)	0.0	5.51
Social words	14.3	9.71
Positive emotions	2.9	4.57
Negative emotions	2.9	2.10
Cognitive processes	14.3	10.77

Table 3. Datum 2: LIWC analysis result on Dr. Lawrence Sellin tweet

LICW Dimensions	Data	Average for Social Media, Twitter, Blog
I-words (I, Me, My)	5.3	5.51
Social Words	0.0	9.71

Positive emotions	0.0	4.57
Negative emotions	10.5	2.10
Cognitive processes	15.8	10.77

The numbers of words in both tweets are slightly different, which is 19 for the first tweet and 76 for the second tweet. The first tweet is from Jim Jordan, one of the senators in the United States of America as data 1. In his tweet, he wrote: "Democrats have no problem requiring and ID for #COVID19 vaccine but a big problem requiring one to vote." This tweet was posted on his tweeter account on April 20nd, 2021, and received 6.026 re-tweet, 250 quoted tweets, and 26.800 likes. The second tweet is from Dr. Lawrence Selline, a retired U.S. Army, Iraq, and Afghanistan veteran colonel, who now focuses on medical research as data 2. On his official account, he wrote: "Does anyone else think it is odd that those who seem to be running the Chinese Communist Party-People's Liberation Army's biowarfare program are responsible for enforcing the Biological Warfare Convention? #CCPVirus #UnrestrictedBiowarfare #OriginOfCOVID19 #UnrestrictedBioweapon." This tweet was posted on April 28th, 2021, and got 1.235 re-tweet, 76 quoted tweets, and 1,646 likes. These two tweets are posting the same topic, which is covid-19.

From the LIWC dimensions, the first is about first-person pronoun I-words (I, me, my) in Jim Jordan's tweet is 5.3 while in Dr. Lawrence's tweet is 0.0; both are still below the average, which is 5.51. The percentage of social words used in the first Tweet does not indicate social words (0.0). Meanwhile, in the second tweet, the generator detects several social words (14.2), which means that the social words in the second tweet are higher than the average of 9.71. Negative emotions and positive emotions for both tweet posts are quite different. In the first tweet, negative and positive emotion equals 0.0, while in the second tweet post, the positive and negative emotions are 2.9. This percentage result means both tweets are lower than the average, with 4.57 for positive emotion and 2.10 for negative emotion. It shows that both tweets are written in a neutral mood since both have the same positive and negative emotion value. The cognitive processes of the first Twitter post are higher than the second post, which are 15.8 and 14.3, while the average is 10.77 means that they write the tweet on purpose.

For the variable summary, the former thinking of the first Tweet post is higher than the second tweet with 92.8 and 67.1, and the average for both is 55.92. While the clout is the opposite of the analytical, the clout that indicates a confident degree shows that the first Tweet result is lower than the second tweet post, which is 5.7 and 87.3, and the average is 55.45. The clout result illustrates the confidence degree of the writer. That is why it shows that the writer of the second tweet is very confident. Authenticity for the second tweet is higher than average, while the first is lower than the first tweet, which is 1.0 and 1.9 of the average percentage, which is 55.66. It seems that both speakers lack honesty. The percentage of emotional tones in the first tweet is lower than in the second tweet, with 1.0 and 25.8, while the average percentage is 63.35; the lower percentage of emotional tones indicates negative emotional tones. It may be confusing because the text is in a neutral mood, but it has a negative tone, this kind of text may also indicate that the text carries an insidious meaning and purpose.

The tweet categorizes as discursive mortality since the degree of this discourse can change its users' and targets' mindsets, or even worst, it can kill them. This discourse not only raises people's emotions and makes them give harmful comments, but it also causes them to commit a crime. For acute toxicity, the LIWC analysis result is nearly the same as chronic toxicity. The difference is that chronic toxicity tweet still has positive emotion, but it is still lower than positive emotion average. The first tweet considers as acute.

DISCURSIVE MORBIDITY

Two data in Table 4 and Table 6 are in discursive morbidity, one in trace toxicity and another in critical toxicity. The LIWC analysis on datum 3 and datum 4 from acute toxicity type was displayed in Table 5, and chronic toxicity in Table 7.

Table 4. Variable summary of the data (Gordon G. Chang tweet)

Variable Summary	Data	Average for Social Media, Twitter, Blog
Analytic	89.4	55.92
Clout	50.0	55.45
Authenticity	7.0	55.66
Emotional tone	1.6	63.35

Table 5. Datum 3: LIWC analysis result on Gordon G. Chang tweet

LICW Dimensions	Data	Average for Social Media, Twitter, Blog
I-words (I, Me, My)	0.0	5.51
Social Words	3.0	9.71
Positive emotions	3.0	4.57
Negative emotions	6.0	2.10
Cognitive processes	0.0	10.77

Table 6. Variable summary of the data (Piers Morgan tweet)

Variable Summary	Data	Average for Social Media, Twitter, Blog
Analytic	97.9	55.92
Clout	94.5	55.45
Authenticity	1.0	55.66
Emotional tone	1.0	63.35

Table 7. Datum 4: LIWC analysis result on Piers Morgan tweet

LICW Dimensions	Data	Average for Social Media, Twitter, Blog
I-words (I, Me, My)	0.0	5.51
Social Words	16.0	9.71
Positive emotions	0.0	4.57
Negative emotions	4.0	2.10
Cognitive processes	0.0	10.77

The first tweet and the second tweet are much different, with the first tweet from Gordon G. Chang, one of the Chines authors, as data 3, while the second tweet is from Piers Morgan, one of the English broadcaster and journalist, as data 4. In Gordon's tweet that posted on March 31st, 2021, he wrote, "The #WHO's report on #COVID19, which looks like it was written by #China's regime, is an embarrassment to scientific community." This tweet consists of 27 words and receives 592 re-tweets, 24 quote tweets, and 1.319 likes. While the second tweet that was posted on October 20th, 2020, Piers Morgan wrote, "BREAKING: The

UK records 21,331 new cases of COVID-19 and 241 new deaths. The 2nd wave is surging dangerously out of control. Please take this very seriously. Don't listen to Covidiots." This tweet contains 29 words and receives 2.143 re-tweets, 250 quote tweets, and 13.800 likes.

From the LIWC dimensions, the first is about the first-person pronoun I-word (I, me, my); Gordon's tweet is 5.3, and Morgan's tweet is 0.0, while the average is 5.51 means that both tweets are below the average. For the social words, the generator found that the first tweet consists of 0.0 social words while the second tweet consists of 14.3, and the average is 9.71, which means that the second tweet is higher than the average. Negative emotions and positive emotions are quite different. The first tweet's negative emotion is 4.0, while the positive emotion is 0.0. Then, the second tweet's negative emotion is 6.0, and the positive emotion is half of it with 3.0. Both tweets are written in a negative mood since the positive emotion is below the average of 4.57, and the negative emotions are higher than the average, which is 2.10. The cognitive process for both tweets is the same with 0.0, while the average is 10.77 means that they write it with negative emotion without any particular purpose except fact and their own tough.

For the variable summary, the former thinking or analytical of the second Tweet post is lower than the first tweet with 89.4 and 97.9, and the average for both is 55.92. While the clout is the opposite of the analytical, the clout indicates a confident degree that shows the first Tweet result is still higher than the second tweet post, with 94.5 and 50.0, while the average is 55.45. The clout result illustrates the confidence degree of the writer. That is why it shows that the writer of the first tweet is very confident. The second tweet's authenticity is higher than the first tweet, with 7.0 and 1.0, while the average percentage is 55.66. It seems that both writers lack honesty. The percentage of emotional tones for the first tweet is lower than the second tweet with 1.0 and 1.6, while the average percentage is 63.35; the lower percentage of emotional tones indicates that the tweet has negative emotional tones. Its coherence with the LIWC dimension, where both tweets have a negative mood, indicates the text may insult people's emotions when they read tweets with a negative tone.

The tweet is categorized as discursive morbidity since the degree of this discourse is unhealthy for the users. It might arouse people's emotions and provoke them to give offensive comments to the Tweet writers. The discursive level is only insulting emotion and damaging the reputation of someone or some groups. For trace toxicity, the LIWC analysis result is nearly the same as critical toxicity. The difference is that the trace toxicity tweet still has a higher positive emotion than the positive emotion average. The second tweet is considered to trace toxicity, while the first is critical toxicity. As seen from its LIWC results, both tweets have high social words, analytic, and clout but low cognitive processes. The dominant emotion is still negative tones even though Trace toxicity has high positive emotions. Discursive morbidity is not as dangerous as discursive mortality since that tweet only insults emotion and damages the reputation of someone or some organization without harming their physical condition.

This study found four pejorative words in each data. In data 1 with covid-19 and data 3 with World Health Organisation (WHO), these words are considered pejorative because they degraded their meaning through the metaphorical process by adding new meaning that still has semantic similarity with the former meaning. The pejorative words are also found in data 2 with bio-warfare and data 4 with covidiots. Both of them degraded their meaning through the narrowing process since both were only used for specific meaning regarding covid-19 pandemic compared to the former meaning that much broader. Those pejorative words have a discursive effect that can change people's perspective about the pandemic and those who handle it. The pejorative words could even harm their psychological and physical condition when used in an inappropriate world.

After analyzing the data using LIWC and finding the pejorative words, this study analyzes the role of ICM in the tweets to reveal the writer's motive in writing the tweet. For the first type of ICM, those four words found on the tweet are considered the proportional type of ICM since those words cannot represent the whole complexity of the pandemic reality. When comparing data 1 and 2, it is found that the word covid-19 and bio-warfare belongs to the metaphorical model of ICM and metonymical models of ICM. For the third model, those words are in a different world but still have a similarity. The similarity proves that no word can exist by itself and may be found differently in society. The word covid-19 is used as the global name of the SARS-Cov2 virus, while bio-warfare defines a war using a biological weapon. These two words are in a different world but are similar: 'biological agents (virus)' and 'disagreement'. In the data context, the biological agent (covid-19) is the media for showing disagreement. From data 1, the writer used covid-19 to show his disagreement with the republic party democrat on their voting regulation, while in data 2, the writer used biowarfare to confront the Chinese Communist Party liberation army to get their confession about the origin of the virus. In the fourth type of ICM model, both words have the same reference: 'biological agent (virus)'.

The metaphorical and metonymical model of ICM is also found in data 3 and 4 through the word WHO and Covidiots. These two words are in a different world but still connected through reference, which is 'stupid people'. The reference also considers the meeting point of both words to show the third model of ICM. In data 3 contexts, the writer considers WHO as stupid because of their inconsistency in naming the virus and making the guideline to fight it. While in the data 4 context, the writer used covidiots to refer to stupid people who make the condition even worst.

THE VARIANT OF TOXIC SPEECH FOUND ON TWITTER

The analysis shows that toxic speech existed on Twitter, but seeing the discursive effect requires a long time and complicated analysis since it deals with how it affects the whole society, not only the internet society. Based on the data analysis, toxic speech has characteristics discovered through the cognitive process, words they use, positive and negative emotions detected using the LIWC program, and pejoration words as the tweet-writer's fundamental focus. LIWC analysis has several characteristics of the toxic speech analysis result. Several characteristics of toxic speech on Twitter are that it always has negative emotionality, low cognitive process, honesty, and authenticity. Sometimes, the tweet-writer also uses social words to show their social concern. Here is the kind of toxic speech on Twitter and its LIWC and ICM analysis results.

The discursive mortality rarely uses the first-person pronoun as the sign of direct pointing to the target, but if it is acute toxicity, the writer tends to point to their target, as seen in datum 1. In contrast, the writer in chronic toxicity tends to make their tweet look universal to satirize the target, as seen in datum 2. It is also happening in the use of social words when it comes to acute toxicity. The tweet-writer tends to avoid using the word with social concern. While in chronic toxicity, the writer used many social words to trigger their target audience to believe their statement. For emotionality, both acute and chronic toxicity tend to hide the emotionality tension. As seen in datum 1 and 2, both tweets are written in a neutral mood with negative and positive emotions having the same percentage. It contradicts the emotional tone that shows a below-average percentage, which means the tweet has a negative tone. The high number of cognitive processes proves those preparation processes; both data show a high percentage of cognitive processes, which means the tweet-writers have already prepared and set their goals before writing the tweet. Those are also supported by the high percentage of the analytic or the former thinking. The cognitive process result contradicts the authenticity, reflecting the honesty and deception, which means that the tweet-writer did their analysis from the secondary data, not the primary data. Those who make their tweet lack honesty and are less reliable to trust. For the clout aspect, which reflected a confident degree, in datum 1, the clout is lower than datum 2, which means the writer of data 1 is not confident with what he writes.

Discursive mortality is slightly different from discursive morbidity since, in this type of toxic speech, the negative emotion and negative tone are dominant with high social words, analytics, and clout but low in the cognitive process for discursive morbidity. On toxic morbidity, both trace and chronic toxicity directly state their emotion, as seen in datum 3 and 4 which the negative emotion and emotional tone are linear and show negative tone. Those supported by the low percentage of the cognitive process mean the writer did not prepare before writing their tweet. However, discursive morbidity has a high percentage of social words, analytics, and clout, reflecting the writer's social concern, former thinking, and honesty. It also shows that the writer in data 3 and 4 researched using primary data and facts to support their argument. The result also shows that toxic speech with discursive morbidity is higher than discursive mortality with a ratio of 2:1 since toxic speech with discursive morbidity usually expresses someone tough but is still dangerous since it can insult people's emotions. In contrast, toxic speech mortality requires more processes to identify its discursive effect as the effects cannot be examined only from the virtual world. The fact is that toxic speech exists on Twitter but demands more analysis to validate it and strategically prevent form poisons by toxic speech.

TOXIC SPEECH MAKES THE PEJORATION WORDS GO VIRAL

The toxic speech worked under the skin, spread harmful content massively through social media, and happened during this coronavirus outbreak. It is the world's fifth pandemic, but only the coronavirus pandemic goes viral because it spread in two different worlds: the definite world and the virtual world. It is no surprise that people also called this pandemic a social media pandemic. It becomes more harmful since, during this pandemic, the one who spread toxic speech is people with power that receive a lot of engagement from Twitter users such as the government, people from related organizations, and some news portals. They tend to write their tweet with purpose and much preparation seen from pejorative words that emphasize their motive. But they were not doing enough research or only did research using secondary data that potentially contained false information. Those are the contributions of toxic speech in spreading the pejorative word on tweeter. Once they use the pejorative word as a hashtag on their tweet, the hashtag will be used by other users whether they agree or disagree with the writer.

Furthermore, the netizen could learn more about identifying toxic speech on Twitter and be more concerned about poisoning themselves by the toxins that spread throughout social media, especially Twitter. Everyone can spread toxic speech without exception as long as they are Twitter users. They possibly spread or get poisoned by the toxic speech. Twitter gives its users free access to explore their applications, but they do not give enough protection to its users from harmful content. Twitter still does not have enough features to directly block harmful content unless the users report it to be blocked. As clear-eyed users, they need to protect themselves from harmful content and false information, including toxic speech. Unconsciously, when someone poisoned by toxic speech in the long term, it will decrease their physical and psychological health and degrade their mental quality. Since in this pandemic era, someone will be more sensitive about specific issues, they cannot control their emotions and end up labeled as a person with a bad attitude.

The data analysis result using LIWC and ICM found that toxic speech has characteristics discovered through LIWC program or the use of pejoration words as the writer's main focus. LIWC analysis can explain several characteristics of toxic speech analysis results that support the first research done by Tirrell to define two characteristics of toxic speech. If the tweet is discursive mortality, the negative emotion and negative tone are dominant aspects, while the clout and authenticity are minor aspects. However, if the tweet is discursive mortality, the social words and clout are dominant. If it has positive emotion, the tweet is on trace toxicity level, but when the positive emotion is below the average, it belongs to critical toxicity. When the analysis uses the pejorative word, the easier way to find the words is to pay attention to the hashtag on that tweet and analyze the metaphorical meaning. The audience engagement towards the tweet, like re-tweet and sharing, also helps to define the audience responses.

The finding shows that toxic speech with discursive morbidity is obtain higher than the discursive mortality with ratio 1:2, since toxic speech with discursive morbidity is nearly the same as hate speech. While toxic speech mortality requires more processes to be identified, its discursive effect as effects cannot be examined only from the virtual world. The fact that toxic speech does exist but demands more processes to analyze.

CONCLUSION

In conclusion, all the analyses found two words categorized which is *covid-19* and *biowarfare* as toxic speech with discursive mortality and two words which is *WHO* and *Covidiots* categorized as toxic speech with discursive morbidity. The LIWC program is used to identify toxic speech since it shows different characteristics at every discursive level. The toxic speech also can be identified by using pejorative words that usually use as the hashtag on the tweet and then interpreting the ICM role to convey its real meaning and the writer's motive in writing the tweet. The result proves that discursive morbidity is the type of toxic speech frequently spread on Twitter during the coronavirus outbreak. The massive data exchange on Twitter and the characteristic of toxic speech that worked under the skin made this pandemic viral and deliberately formed new cyberculture on Twitter. This cyberculture is mostly created by influential people on Twitter who write their tweets on purpose but without reliable research. Then, it is widely used by other Twitter users by quoting, re-tweeting, sharing the tweet, and using the same hashtag with influential people. It becomes harmful when the tweet uses pejorative words, which could contain toxins and potentially poison many people who write and read it.

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