SOTICS 2024

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SOTICS 2024

Forward

The Fourteenth International Conference on Social Media Technologies, Communication, and Informatics (SOTICS 2024), held on September 29 – October 3, 2024 in Venice, Italy, was an event on social eco-informatics, bridging different social and informatics concepts by considering digital domains, social metrics, social applications, services, and challenges.

The systems comprising human and information features form a complex mix of social sciences and informatics concepts embraced by the so-called social eco-systems. These are interdisciplinary approaches on social phenomena supported by advanced informatics solutions. It is quit intriguing that the impact on society is little studied despite a few experiments. Recently, also Google was labeled as a company that does not contribute to brain development by instantly showing the response for a query. This is in contrast to the fact that it has been proven that not showing the definitive answer directly facilitates a learning process better. Also, studies show that e-book reading takes more times than reading a printed one. Digital libraries and deep web offer a vast spectrum of information. Large scale digital library and access-free digital libraries, as well as social networks and tools constitute challenges in terms of accessibility, trust, privacy, and user satisfaction. The current questions concern the trade-off, where our actions must focus, and how to increase the accessibility to eSocial resources.

We take here the opportunity to warmly thank all the members of the SOTICS 2024 technical program committee, as well as all of the reviewers. We also kindly thank all the authors who dedicated much of their time and effort to contribute to SOTICS 2024.

We also gratefully thank the members of the SOTICS 2024 organizing committee for their help in handling the logistics and for their work that made this professional meeting a success.

We hope that SOTICS 2024 was a successful international forum for the exchange of ideas and results between academia and industry and to promote further progress in the area of social eco-informatics. We also hope that Venice provided a pleasant environment during the conference and everyone saved some time for exploring this beautiful city

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A Study into the Disruption of Social Media Platforms on Social Gatherings and Public Places

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Abstract—Web 3.0 through social media (SM) has changed user experience and attention on the Internet enabling the generating of personalized content. Numerous studies have been undertaken on the dual impact of SM on education, and academic performance as well as the factors that influence the use of SM. However, the disruption of SM platforms in public and social gatherings has not been investigated adequately as SM platforms evolve. To instantiate this research, quantitative research methodology was used to investigate the reasons, effects, economic and social factors, and feasible measures for the use of SM platforms in social and public gatherings. The study draws its sample from a selected higher education institution (university and college) in the North West Province, South Africa. The study utilized digital questionnaires and 70% were recorded from the population size of 375 students. The data analysis and interpretation were done using Statistical Package for Social Science (SPSS) involving descriptive and inferential statistics. The research findings indicate that COVID-19 and technological improvements were the main reasons for SM use in gatherings which mostly affects interpersonal communication and personal identity. The finding also suggests that the regulations of COVID-19, the advancement of technology, political unrest, and economic instability are the pioneer factors that accelerate the use of SM. Results show SM disruption programs together with digital detox and self-control are feasible measures to curb the use of SM platforms in social gatherings and public places (settings).

Keywords-Social media; Disruption; Web 3.0; Facebook; SM platforms; COVID-19.

I. Introduction

Web 2.0 (the second generation of the World Wide Web that evolved to support social interaction in the digital space) has significantly changed traditional settings and participation [1]. Social media (SM) platforms (Facebook, X formally known as Twitter, Instagram, and WhatsApp) disrupt attention, reduce face-to-face interaction, and promote the absence of direct communication and intellectual engagement [2]. According to Bhandarkar and Pandey [3], SM deteriorates cognition and leads to the destruction of attention and later negative effects on one’s day-to-day physical and social activities. A study was done by Bhandarkar and Pandey [3] appends on Subramanian [2] findings that the more people get attached to their smartphones the less they will be socially and directly active. Human behaviour is now fast-paced, people no longer wait and greet one another when they are with their friends and acquaintances [2]. SM connects us with long-lost friends, recent trends, and daily news feeds and allows us to market our products and services digitally [4]. However, the SM does not maintain much of the traditional participation and association we once had before the revolution of the World Wide Web (WWW) rather it has significantly changed our day-to-day traditional settings and participation [1]. The study investigates the disruptions of SM use in social gatherings and public settings and recommends feasible activities to respond to SM use in gatherings. The rest of the paper is arranged as research methodology, literature review, problem statement, data analysis and discussion of the findings, research summary and future study, implications of the study, and conclusion.

II. Research Methodology

The main two research types include quantitative and qualitative. Quantitative research quantifies data collected to provide unambiguous results. The numerical data collected can be virtualized by using graphs and tables. According to Goertzen [5], quantitative research analyses structured data that can be modeled numerically. This study needs to find out how to use figures to deduce relationships, the context of the setting, and SM use. Computer applications including Statistical Package for Social Science (SPSS) allow manipulation of data to provide numerical results. Therefore, SPSS was used as a data manipulation technique in this study. The quantitative method is best for analyzing data gathered through questionnaires as the respondent is guided by the questions which the researcher wants answers for.

A. Research method

Quantitative research uses pre-programmed parameters for questionnaires and the survey results can be represented numerically. The method is relevant to building accurate and quantifiable results that can later be modeled with statistical analysis for experiments to provide reliable numeric results on the study [5]. Allen and Titsworth [6] append on Goertzen's [5] research that quantitative research provides practical and user-friendly tools to apply statistics. Therefore, in this study, the quantitative research method was used since the study was mainly concerned with investigating the disruptive nature of SM platforms in social gatherings and public settings.

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B. *Data source*

The researchers to build an understanding of a subject concern need to identify sources of data from which a study will be relied on to make informed decisions. Primary and secondary data were used in this study. The primary data sources include questionnaires, surveys, experiments, and observation. For this study, questionnaires were used as a means of primary data source. According to Hox and Boeije [7], whenever primary data is collected new data is added to a store of knowledge. Academic journals, articles, and books are the sources of secondary data. Secondary data collection is the use of existing findings and research data to answer the questions of a new study [8].

C. *Data collection method*

The study used standardized questionnaires as a data collection instrument, which was developed through Google Form. The standardized questions were vital that they helped in identifying and counting the frequency of certain occurrences, behaviour, experiences, and opinions of the respondent. Google Forms allowed the researchers to pre-program closed-ended questions that the respondents needed to answer from a list of possible replies. Rowley [9] describes questionnaires as a series of open and closed questions that the researcher invites the respondents to answer. The Uniform Resource Locator (URL) was therefore sent to invite the targeted/sample population of students in the selected high education institutions (HEIs) in Mafikeng through WhatsApp, Email, and Facebook to attain a greater sample size. Online questionnaires are effective and efficient in that the sample population can be reached less costly as the researcher does not have to take field trips [10].

D. *Questionnaire format*

Table 1 below represents the layout/structure of questionnaires categorized into sections. The respondents first provide their demographic information and consent to continue with subsequent study sections (section 1 – section 5).

TABLE I. QUESTIONNAIRE STRUCTURE

Section 1	Question the respondent about the demographical information. This includes age, education, country, race, province and city.
Section 2	Question the respondent about their understanding of SM networks and their primary uses.
Section 3	Question the respondent about the disruption of SM use in social gatherings
Section 4	Question the respondent about the effects of SM use when in social gatherings
Section 5	Question the respondent about the feasible measures that can be put in place to encourage users to avoid using SM in social gatherings.

E. *Population and sampling method*

A sample is a subset of the population chosen to represent the entire population affected by the study. Acharya and Prakash [11] insist that the effective strategy is to investigate the problem that affects the whole population. When a problem that affects the whole population is known, representation can be deduced in the form of a sample that meets the characteristics of the problem domain noted from the entire population. The following formula was introduced by Krejcie and Morgan [12] was used in this study to calculate the sample size:

$$s = X^2NP(1-P) \div d^2(N-1) + X^2P(1-P).$$

s = required sample size.

X^2 = the table value of chi-square for 1 degree of freedom at the desired confidence level (3.841).

N = the population size.

P = the population proportion (assumed to be .50 since this would provide the maximum sample size).

d = the degree of accuracy expressed as a proportion (.05).

Figure 1. Krejcie and Morgan (1970)

The Table 2 matrix which was developed by Krejcie and Morgan [12] provides pre-calculated sample sizes for populations of different sizes. This study targeted the total population of 13 266 (11 657 from NWU Mafikeng and 1 609 from Taletso TVET College) registered students in the 2021 academic year. According to the table matrix, the sample target was 375 participants, and 263 were involved. Below, Table 2 shows the sample targets of different population sizes as introduced by Krejcie and Morgan [12].

TABLE II. THE SAMPLE SIZE

Table for Determining Sample Size from a Given Population

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377

The population sample size is students who are constant users of social media for academic and non-academic activities. The sample size focused on students in Mafikeng from the North-West University and Taletso TVET College with an estimated sample size of 375. The participants in the involved institutions possess the experience and information that aid the objectives of the study and a consent letter was used in the data collection. The study and its data instrument were approved.

III. LITERATURE REVIEW

This section of the study presents the existing literature studies exploring the research gaps.

A. *The disruption of social media platforms in social gatherings and public places*

Social media can be said to be disruptive because of its innovative processes and application in human lives. Millar and Lockett [13] describe a disruption as an innovation or change that renders the former or predecessor task ineffective or inefficient concerning the latter. By critically examining the description of disruption by the authors about the research questions, technology brought about by Web 3.0 from Web 2.0 has severely changed SM users' behaviour. Potluri and Vajjhala [14] describe Web 3.0 technologies as the interactions of web technologies and artificial intelligence (AI) subsets, namely the representation of knowledge. Web 3.0 is a personal assistant that connects SM users with information on the Internet and practically everything [15]. Web 3.0 is the latest multimedia interface technology to the resources on the internet. It provides personalized content service to improve user experience and capabilities for collaboration, participation, and information sharing. Social networks (Facebook, Instagram, X (Twitter) or WhatsApp) run on the above-mentioned latest technology (Web 3.0) with built-in APIs (Application Programming Interface) for mobile app support [16].

The advancement or change in technology continues to divide individuals from participating physically even when they are physically connected. A study done by Oksa and Kaakinen [1] indicates that many people in social and public settings are connected but they are not. SM disruption has changed the way people ought to communicate and practice their respective values. Chukwuere and Chukwuere [17] indicated that continuous usage of SM isolates one another and changes social norms and cultures. According to Mushtaq and Benraghda [18], university students widely use SM in class which affects their personal and academic lives. Furthermore, students appear to be the most vulnerable to this challenge due to their capacity to understand and interact with recent SM technologies. During contact classes, especially in the lecture room, the probability of finding two to three students in the same row sitting with their heads facing down to their smartphones was very likely. Peper and Harvey [19] observed university students as they entered the lecturer's room, many students who entered the venue were on their phones they could not communicate with their friends since they were scrolling, texting, and clicking on their smartphones. Lau [20] states that students are likely to use multiple mediums at a time and the potential influence of SM multitasking has been poor communication and association.

B. The economic and social factors that accelerate the use of SM in public and social gathering

The latest motivation for and use of SM platforms has been caused by the 2019 pandemic. Countries around the globe including South Africa introduced measures to restrict traveling and social gatherings to respond to a deadly virus known as COVID-19 [21]. In South Africa, the Republic President (Cyril Ramaphosa) introduced methods that prohibit social gatherings of any kind, especially during alert Level 5, to contain the spread of the unprecedented virus. News feeds were channeled through social networks for enough coverage about the latest development of coronavirus. According to Liu and Liu [22], the regulations left many people with no option but to use SM to claim back their withheld right of movement and gathering. Universities across the country, including North-West University, were using Facebook and other platforms to reach students about the development of COVID-19 and other curriculum information that is in line with national regulations. Hosen and Ogbeibu [23] state that higher education institutions realized the value of social networking sites and the need for student motivation has encouraged students to be updated with content posted on university sites to bolster learning performance. Students are now vulnerable to being on SM when they are in public spaces due to the changes in social life and teaching and learning methods [24]. The regulations isolate individuals from one another, and SM disables direct communication and participation in a physical setting. The current rate of unemployment in South Africa has contributed to social loss and low self-esteem in social settings and the affected rely on SM platforms to look for opportunities.

According to Feuls and Fieseler [25], unemployed individuals tend to use SM in social settings to cherish their social support networks and restore their dignity. Being unemployed with no means to meet basic needs affects social contact and leads to psychological problems and many believe that SM is a gateway to be socially participative. Feuls and Fieseler [25] further say employment is not only a means to meet basic needs and earn a living but also a network that facilitates the development of social relationships and human empowerment. Therefore, being unemployed diminishes social contact and leaves the affected with no choice but to have their faces down to their phones' screens to avoid being downgraded and humiliated by a conversation that may constantly divert them back to their problems. Peterie and Ramia [26] research found that some individuals who are socially distracted by SM in social gatherings have gone through the socio and emotional realities of being unemployed. Not only does unemployment affect communication in social gatherings due to anxiety and low self-esteem but the context in which communication takes place may also deprive individuals from participating as a result of interests as well as language barrier.

C. The negative effect of using Social Media platforms on social gatherings and public places

A shift from the industrial age to the information age has increased the level of dependency on digital platforms (services) to socialize daily. Krishna and Jayanthi [4] found that university students rely on information they receive on SM which limits their learning and potential research capabilities. Social networks make students to be reactive rather than proactive and that limits their understanding of a subject concern. Rithika and Selvaraj [27] study indicates that students use SM for personal reasons when they are in group discussions and topics that differ from the course work. Universities have transitioned to online learning to comply with then COVID-19 regulations and to complete the academic year, but students are not well prepared, and they continuously participate in non-academic activities that consume much of their study time [28]. Nowadays in universities, it is difficult to imagine a university student who, at least once a day, does not get to their phone for updates on social networks when he/she is engaged in conversation [29]. The modern reality costs the students a fortune during class, and it further affects other students whom they keep on asking for information that they have missed due to their lack of concentration. According to Kolan and Dzandza [30], SM use during class affects the performance of students and later they cannot maintain scores required by funders to sustain bursaries. Disruption of SM in public and social settings hurts one's culture and values.

It is believed that colonialism has robbed us of practicing our cultures and values. But to date, SM use also has serious repercussions that are hidden and which, gradually so, distance us from having traditional engagement to maintain our value of structure constructed through our elders. Amedie [31] insists that SM use in public is depriving us of the trust people had and the comfort people always found from one another through direct communication, substituting the direct fellowship of emotional support humans once portrayed from one another with virtual connection. SM progressively segregates humans from practicing their cultures and that will later construct a cultural bomb. A cultural bomb is a situation whereby individuals seek for their own identity and by that time information and practices will be lost especially when there is less research and publication in the cultures in question. Lyu and Zhang [10] state that technological advancement in social and economic activities has without doubt implicated the culture of human civilizations. Consciousness and hermeneutics play a significant role in addressing cultural implications brought about by SM technology that rob individuals from practicing their cultures and values when they are in numbers. According to Tripathi [32], society has revolved around technological culture and antisocial beings that depend on social networks for new updates and daily trends.

D. The measures to discourage the disruptive nature of social media usage in public settings

SM continues to separate humans from traditional communication in social space. Students at institutions of higher learning, ordinary SM users, workers, and church congregants use SM as a dialogue through the power of ever-embraced technology. Very often, they tend to use SM (Facebook, WhatsApp, or X (Twitter)) when they are physically engaged in a conversation. As a result, human engagement is negatively affected. The following measures may be feasible to enlighten users of the disruptive nature of using SM platforms when they are physically engaged.

SM users must disrupt their normal routine of SM use to alleviate themselves to change a habit. Modern Application that comes with smartphones allows users to limit or stop running apps by simply setting up a smartphone to "do not disturb" mode when they are occupied [33]. Individuals are also responsible beings who need to take responsibility for their actions by setting goals for SM and the time limit as well. According to Kurniasanti and Assandi [34], 'do not disturb' applications do not have a timer to restrict the launching of an App before the time set by the user to avoid being distracted. Users can continually gain access by disabling the "do not disturb" Application and continue getting distracted on SM in a social environment. However, one can engage one's friends and associates before a meeting that they will not be available for a certain time and put the phone on silent if the "do not' mode is not effective.

IV. Problem Statement

SM platforms allow users to create, post, and share information on the internet through the power of Web 3.0 technology. To date, numerous studies undertaken mostly focus on various uses of SM, its impact on social behaviour, education, and academic performance as well as the positive and negative impact, the factors that influence the usage, ethical usage, and many more [17] [35][36]. However, SM use in public and social gatherings has limited research since much of the research areas in SM are on personal level concerns rather than on social and public challenges. Very often, people tend to use SM (Facebook, WhatsApp, or Twitter) when they are physically engaged in a conversation and during social or public settings. As a result, traditional communication and human engagement are negatively affected.

Main research question

Why do students get disrupted by SM platforms during social gatherings and public settings?

The following are the secondary questions developed from the problem statement above:

- Why do many students connect to SM when they are in social and public gatherings rather than having direct communication?
- What are the economic and social factors that influence the use of SM in public and social settings?
- What are the effects of SM use in social gatherings?
- What measures can be put in place to encourage students to understand the disruptive nature of SM in public settings?

Research aim, and objectives

The study seeks to:

- Investigate the disruption of SM platforms on social gatherings and public spaces.
- Identify the economic and social factors that influence the use of SM in a public and social setting.
- Describe the negative effects of using SM platforms on social gatherings and public places.
- Recommend measures that are feasible to be put in place to encourage individuals to understand the disruptive nature of SM use in social and public settings.

V. Data Analysis and Discussion of the Findings

In this section, the researchers discuss the results found in this research and are guided by the research objectives. The study findings are derived from the data analysis covering the descriptive analysis, correlations, and Chi-squared tests, and the discussions are backed by the existing literature.

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A. *Objective 1 - To investigate the disruption of social media platforms on social gatherings and public spaces*

The study findings showed that students post and share information with their friends when they are on SM platforms. Table 3 presents that 41.1% (108) of students sign into SM platforms because they are not interested in the subject concern. Of 263 respondents, 20.5% (54) strongly agree that they connect to social networks because they are not interested in a conversation taking place during a gathering. The 3.8% and 17.1% of respondents do not agree that students sign into social networks during gathering because they are not interested in a conversation and the 17.5% (46) could not decide whether students are interested or not interested.

TABLE III. STUDENTS ARE NOT INTERESTED IN THE SUBJECT CONCERNED

	Frequency	Percent	Cumulative Percent
Strongly disagree	10	3.8	3.8
Disagree	45	17.1	20.9
Undecided	46	17.5	38.4
Agree	108	41.1	79.5
Strongly agree	54	20.5	100.0
Total	263	100.0	

Based on the data analysis found in Table 3, many of the students signed into SM platforms because they were not interested in the subject concern in the discussion. That could be attributed to the fact that students come from different backgrounds, generations, and cultures and have different values. For example, not all students participate in extracurricular or political activities therefore a gathering that is geared up by the activities has the potential to influence a student to sign in to social media to find his/her interest. It was also found that more than a third of students (39.54%) are serviced by the personal content provided in SM which relates to their interests. The study findings conform to Balaji and Rao's [37] results that association rule mining (Application Programming Interface) finds the related patterns from data generated by users and later classifies data into user interests for easy reference and relevant user experience.

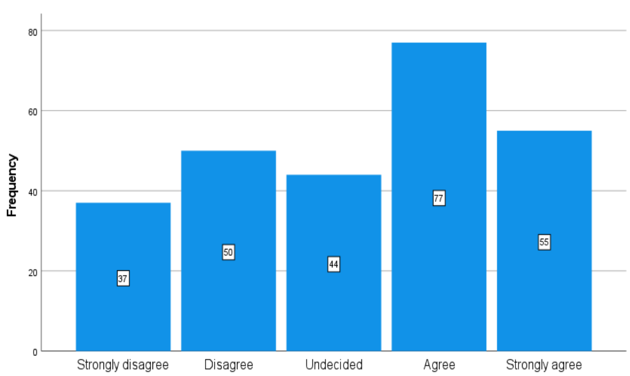

Figure 2. COVID-19 pandemic regulation

Figure 2 shows that 77 respondents (29%) of 263 students who participated agree that COVID-19 regulations which restricted traveling and gathering of any form have caused students to sign into SM platforms extensively and even during social gatherings. 55 (21%) strongly agree that social networks were the only platforms that many students relied on during hush lockdown levels and now that regulations have been relaxed students are accustomed to using their devices in social environments. The study findings also indicate that there are only 87 (37 and 50) respondents who do not agree and that accounts for 33.08% which is lower than the percentage of students who agree, 50% (29% and 21%). Hussain [38] also found that social networks such as WhatsApp, Instagram, X (Twitter), and Facebook were the major sources of information and news feeds to the public during the early days of the COVID-19 lockdown.

In summary, the study also found that COVID-19 regulations have contributed significantly to the use of social media platforms during gatherings since students could not travel and do any form of gathering. The regulations led to an excessive use of social media. The study further indicates that there is a relationship between COVID-19 and social isolation during gatherings. From the Chi-squared test results, the accepted hypothesis was that the COVID-19 pandemic has a relationship with social isolation during gatherings. The results mean that the COVID-19 pandemic causes students to isolate themselves to avoid getting infected and they rely on their phones to connect with others.

TABLE IV. INTROVERT AND SHY

They are introverted and shy to engage in social gatherings			
	Frequency	Percent	Cumulative Percent
Strongly disagree	13	4.9	4.9
Disagree	29	11.0	16.0
Undecided	57	21.7	37.6
Agree	96	36.5	74.1
Strongly agree	68	25.9	100.0
Total	263	100.0	

The extensive use of SM platforms has more impact on users who are introverted and shy. Some scholars have found that shy individuals are always preoccupied with their smartphones during social interactions [39]. In Table 4 the study found that of 263 respondents 96 (36.5%) respondents agreed that individuals who always sign into SM network are introverted and shy during social and public gatherings. Introvert and shy individuals find social networks as a gateway to hide or exclude themselves during social interactions and public settings. The result in Table 4 also indicates that 25.9% of respondents strongly agree with the question.

The study results indicate that most scholars believe that personality has an impact on interpersonal communication. It was found that students who are introverted and shy cannot cope with the social environment and that any social gathering causes irritation. Students with such personalities find social media platforms as social network gateways. A study by Appel and Gnambs [39] indicated that shy

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individuals are always preoccupied with their smartphones during social interactions. The overall findings show that students believe that social irritation during gatherings could be a result of shyness and introversion. The results of the study therefore offer support to the existing findings that put much emphasis on the individual disruption of SM platforms rather than the effects SM usage has in social and public environments.

B. *Objective 2 - Identify the economic and social factors that influence the use of SM in a public and social setting*

The study found that advancement in technology influences the disruption of SM platforms in gatherings. Table 5 indicates that 5.4% of respondents (2.7% and 2.7%) disagree but 87.1% (49.8% and 37.3%) of respondents agree. Respondents who strongly agree are voluminous as opposed to those who disagree or strongly disagree. Baek and Lee [40] found that the more there are innovations in technology, the wider will be the impact on numerous societal activities. Mobile applications have background apps that store user-key-strokes each time an application is launched to provide relevant content whenever an app is launched again [41]. Advancements in technology have transitioned student's behaviour into anti-social beings.

TABLE V. TECHNOLOGICAL ADVANCEMENT AND SMARTPHONES' NEW FEATURES

	Frequency	Percent	Cumulative Percent
Strongly disagree	7	2.7	2.7
Disagree	7	2.7	5.3
Undecided	20	7.6	12.9
Agree	98	37.3	50.2
Strongly agree	131	49.8	100.0
Total	263	100.0	

The research found that the temporary lease of the radio frequency spectrum by the Independent Communication Authority of South Africa (ICASA) (2020) had an impact on social media use [42]. The lease improved network connection and decreased data cost to improve user experience. The study further indicates that a total of 74.04% of students agree that network connection in the early days of lockdown was bad but not after the temporary lease of spectrum came into effect. It was also found that technological improvements have a severe impact on continuous social media use during social gatherings. The study found that there is a relationship between poor communication during social gatherings and technological advancements. From the Chi-squared test results, the accepted hypothesis was poor interpersonal communication is influenced by technological advancements. The results meant that technological advancements have an influence over day-to-day student communication, and it causes less interpersonal communication.

The study found that universities across the country, including North-West University, have been relying on Facebook business accounts to reach out to students about academic information that is in line with national regulations. It was further found that most students, 86.3% (46% and 40.3%) believe that the destruction of social media in gatherings is also caused by lockdown, hence the universities were allocating mobile data to students to continue teaching and learning. The regulations left students with no option but to use SM to claim back their withheld right of movement and gathering [22].

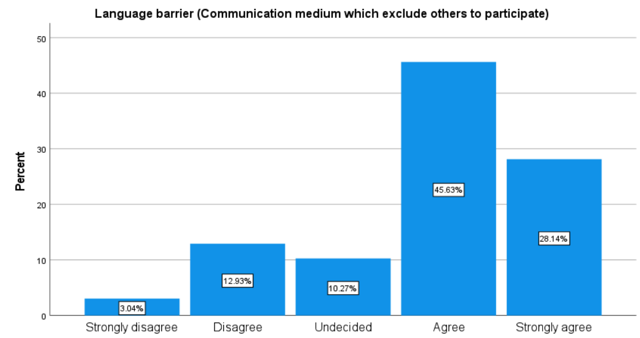

Figure 3. Language

Language barrier emanates when one experiences some difficulties when trying to decode or encode a message during conversation. The language barrier is recently being addressed through translation and virtually revealed by the work of interpreters [43]. The study has found that language barriers influence students to be on their smartphones during social gatherings as a result of having no understanding of the language and subject concerned. Figure 3 indicates that more than two-thirds, 73% of participants (45.63% and 28.14%), agree that they switch to their SM accounts when they are not familiar with the topic and language being used in a given setting. The findings reveal that a study done by Ribeiro [43] supports these findings that students to participate in a conversation will need an interpreter to decode or encode all messages and the probability that meaning may be lost during interpretation by a third party is very likely to be lost. Language barriers prevent students during gathering who hold potentially similar interests, concepts, customs, and beliefs from directly participating with each other. In this research, there were fewer respondents (3.04% and 12.93%) who opposed the language barrier as a social factor that influences social media use in gatherings.

In summary, the language barrier was found in this study to be the most influencer of social media use in social gatherings. The finding shows that many students had identified language barrier as a main cause of communication challenges. The study also indicates that there is a relationship between poor interpersonal communication is influence by language barrier in social gatherings. The study results indicate that addiction to social media has contributed to social disruption in gatherings.

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TABLE VI. ADDICTION

	Frequency	Percent	Cumulative Percent
Strongly disagree	7	2.7	2.7
Disagree	18	6.8	9.5
Undecided	30	11.4	20.9
Agree	116	44.1	65.0
Strongly agree	92	35.0	100.0
Total	263	100.0	

Addiction is realized when one finds it difficult to deviate from engaging in certain behaviour or substance. Consumption today increases demand tomorrow [44]. From Table 6, 44.1% and 35.0% of participants agree that the use of SM disruption in gathering is addictive and hinders effective communication and collaboration. A study done by Alzougool [45] indicates that of 397 participants 38.5% were addicted to Facebook and results were associated with respondents who entertain, escape (seek distraction), and pass time when they are physically engaged. Alzougool [45] further found that 153 of 397 respondents were Facebook addicts which reflected a high percentage of the studied sample. The study established that most students use Facebook for social networks and that accounts for 82.4% of respondents. It is therefore evident that the findings in Table 6 align with Alzougool [45], and Karim and Haque [46] findings that most SM users are addicted to Facebook. Only 9.5% (2.7% and 6.8%) of respondents disagree and that figure is many times lower when compared with respondents who agree that addiction to SM platforms influences social places. Table 6 shows that most students are addicted to their phones and cannot cope well without having them in social gatherings.

C. Objective 3 - Describe the effects of using SM platforms in social gatherings and public places

The research found that the more students are signing to social networks there is less participation. Figure 3 indicates that 73.67% (42.5% and 31.17%) of students have recognized that social media use in gatherings disturbs participation and leaves no room for effective information sharing. The results are supported by Chukwuere and Chukwuere's [17] findings that SM disrupts the social lifestyle and interactions in society. The findings explicitly prove that most noticed that SM negatively affects social interactions and participation. Participation is useful, especially to parties who have never met before to exchange ideas, and life experiences and build on top of each other's ideas. On the contrary, Students are rather satisfied when they are on their phone screens and participating virtually. From the chi-squared test, the accepted hypothesis was that poor interpersonal communication is influenced by language barriers in social gatherings. The chi-squared results mean that students sign into SM because they may not understand the language being used during communication.

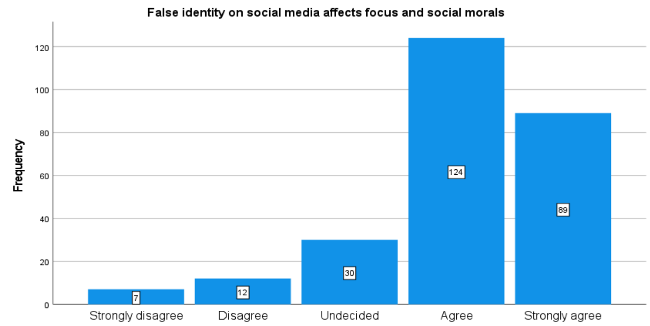

Figure 4. Identity

The study found that most participants agree that SM changes users. Of 263 respondents 213 (124 and 89) or 80.9% participants confirmed that the disruption of SM platforms leads to false identity. Jan and Soomro's [47] findings reveal that 88% of respondents sign into social networks to make social comparisons and the study further found that 98% of the comparisons relate to upward comparison. From Figure 3 most participants 89 strongly agree that upward comparisons change the identity of SM users and later cause them to feel unfortunate and negative about themselves. The researchers also found that an increase in SM usage results in a decrease in self-esteem. False identity influences SM users to feel less privileged and be ungrateful for their current status and well-being [47] [48]. Jan and Soomro [47] further found that feeling negative about oneself has a direct impact on self-confidence and appreciation of oneself. The bar graph also shows that only 19 (7 and 12) participants (7.22%) disagree and that is the lowest number when compared with other responses. It is therefore evident that using SM platforms in gathering may later influence the user to engage in activities that are characterized by false identity and that affect self-esteem and self-confidence for personal development and self-motivation.

Students are influenced by other SM users and make social comparisons [47] [49]. Life comparison influences students to pretend to be people they are not in other to fit into a digital society. Mobile applications such as Instagram are mostly favored by students to display their beauty. Students tend to feel less capable and privileged as opposed to others on the digital social network.

D. Objective 3 - Recommend feasible measures to be put in place in order to encourage individuals to understand the disruptive nature of SM

The fourth objective was intended to identify possible measures which have the potential to assist affected students. Syvertsen and Enli [50] describe digital detox as a means to take a break from participating in SM and other online activities for a certain period and restrict the use of smartphones and digital tools. Individuals are responsible beings who need to take personal responsibility to balance risks and pleasure [50] [51]. The study also found that, according to Figure 4, a total of 87.02% (40.84% and 46.18) students accept that taking a break from participating in SM platforms and other online activities for a certain period and restricting the use of smartphones and digital tools can curb SM platform addiction. The findings support Syvertsen and Enli's [50] research that SM and Internet users must take a break to balance risk and pleasure.

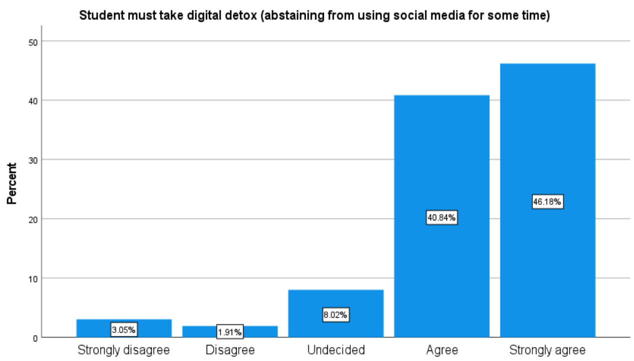

Figure 5. Digital Detox

The study has found that social media detox is a feasible recommendation for students to practice for them to abstain from using social media during gatherings. The result aligns with Syvertsen and Enli [50] and Anderson and Rainie [52] findings that Individuals are responsible beings who need to take personal responsibility to balance risks and pleasure. From the Chi-squared test results the accepted hypothesis is that peer pressure and social media disruption programs associate and can help students to alleviate social media use during gatherings. That means social disruption program has an impact on peer pressure and students can benefit more if an awareness campaign is started.

A digital detox can help students refrain from connecting to SM platforms focus on realizing their potential and rebuild their traditional and cultural norms which were not applicable on social networks. The results show that finding a new hobby can be an alternating way of detoxing and that was supported by a total of 85.5% (35.7% and 49.8%) of students who participated. New hobbies may include, among other things, sports, reading, researching about the disruption of social media, or spending time with family.

TABLE VII. SOCIAL MEDIA DISRUPTION PROGRAMS BY THE DEPARTMENT OF COMMUNICATION AND DIGITAL TECHNOLOGIES

	Frequency	Percent	Cumulative Percent
Strongly disagree	8	3.0	3.1
Disagree	6	2.3	5.3
Undecided	26	9.9	15.3
Agree	123	46.8	62.2
Strongly agree	99	37.6	100.0
Total	262	99.6	

Table 7 shows the number of responses to the recommended measure to discourage the use of social SM platforms during social gatherings. Of 263 respondents, a total of 222 (123 and 99) (84.4%) agree that social media awareness programs have the potential to encourage communication during social gatherings. The implementation of such programs can be from the national level by the South African of communication and digital technologies. According to the Department of Communication and Digital Technologies (2019), the mandate of the minister is to "promote constitution and its values in schools, awareness campaigns, public engagement, and dialogue". The study also indicates that respondents who disagree with awareness programs account for 5.3% (3% and 2.3%). The minister of digital technologies must design a program that is aimed at educating SM users about the impact of SM use in public places.

The study has found that most students believe that the governing party must take responsibility for the continuing SM disruption in gatherings since it is the government that approves technology that is being used in households and industries. The Chi-squared test results indicate that the accepted hypothesis was that peer pressure and social media disruption are associated.

VI. RESEARCH SUMMARY AND FUTURE STUDY

The study used digital questionnaires to remotely invite students to participate in the study and the collected sample data is 263. Below a summarized responses to research questions.

- The respondents are made up of students from North-West University (Mafikeng) and Taletso TVET College (Mafikeng).
- The respondents use social media for creating, posting, and sharing information with friends for new updates.
- The continuous use of SM in social gatherings affects participation in group discussions and leads to false identity.
- Students sign into an SM account because the language or medium used in a group is not understood.
- Peer pressure affects students to join into the new normal. The environment of addicted SM users attracts students to fall into it.
- The lockdown regulations had caused Institutions of Higher Learning to adopt new teaching and learning and shift to online learning.
- Institutions of Higher Learning use SM platforms to communicate and share updates with the students.
- Students are attached to SM platforms as a result of online learning and lockdown regulations that prohibit gathering and traveling.
- The advancement in technology and temporary allocation of network spectrum has led to more demand for Internet connectivity and SM participation.
- SM disruption awareness programs, authenticity, and self-control are the recommended measures to mitigate SM disruption in social gatherings.

Implications of the study

The researchers in this field must use these study findings to further include another group that was not part of the study sample. Then this study's results can be tested fairly with findings from other population groups. The focus should be shifted from researching the personal impacts of social media to resolving the damage social media creates in our societies and public places. Researchers must further incorporate both qualitative and quantitative to understand the contradictions between quantitative findings with qualitative results. The mixed approach would reflect the participants' points of view and give them a chance to raise their voices based on their experiences.

VII. CONCLUSION

The role of social media in social gatherings of students can't be underrated. In conclusion, this study sheds light on the significant impact of social media disruption on social gatherings and public places, particularly among students in higher education institutions. The findings highlight the pervasive influence of peer pressure, social comparisons, and the COVID-19 pandemic on the excessive use of social media platforms during gatherings. Individuals often resort to social media to navigate social interactions, create false identities, and seek validation, leading to potential negative consequences on self-esteem and personal development.

Moreover, the study underscores the importance of implementing measures such as digital detox programs, awareness campaigns, and promoting self-control to mitigate the disruptive nature of social media in social settings. Recommendations for encouraging individuals to understand and address the detrimental effects of social media include advocating for authenticity, self-regulation, and balanced use of digital tools.

Moving forward, future research in this field should consider incorporating a mixed-methods approach to capture a comprehensive understanding of the complexities surrounding social media use in public spaces. By exploring both quantitative data and qualitative insights, researchers can delve deeper into the nuanced experiences and perspectives of individuals affected by social media disruption. Ultimately, addressing the challenges posed by social media in public places requires a multifaceted approach that prioritizes individual responsibility, social awareness, and the promotion of healthy digital habits.

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Analyzing Key Network Structures of 2022 Malaysian General Elections from the Lens of Instagram

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***Abstract*—This study explores social media's role in shaping political discourse during the 2022 Malaysian general election, focusing on Instagram as a key platform. Using an approach that combines Contextual Focal Structure Analysis (CFSA) and topic modeling, we analyze 53,116 Instagram posts from the election period. Our research aims to identify influential actors, map information flow patterns, and uncover dominant themes in online political conversations. The CFSA method reveals intricate networks of journalists, media houses, politicians, and political parties, highlighting the complex interplay between media and politics in the digital sphere. Our findings demonstrate social media's significant impact on Malaysia's political landscape, showing how digital platforms facilitate the convergence of traditional media, political actors, and public opinion. We observe distinct patterns of information flow and influence, with certain focal structures dominating the discourse. The study also uncovers key topics that resonated with the Malaysian electorate during the election. This research contributes to understanding digital democracy in Malaysia and offers insights into the evolving nature of political communication in the social media age. Our methodology provides an approach for analyzing complex digital interactions in political contexts, with potential applications beyond the Malaysian case study.**

Keywords- *Social Network Analysis; Malaysia General Election; CFSA.*

I. Introduction

The Malaysian political landscape has been characterized by instability in recent years, particularly during general election periods. This volatility stems from a complex interplay of political, societal, and economic factors, including the country's rich racial and religious diversity [1]. Amidst this backdrop, social media has emerged as a powerful force in reshaping Malaysia's political discourse and mobilizing public opinion.

This research paper aims to analyze Malaysian election politics through a novel approach combining contextual focal structure analysis and topic modeling. Our study seeks to identify key political figures in Malaysia and understand the primary topics they discuss, particularly in the context of election campaigns and their aftermath.

By employing contextual focal structure analysis [2], we aim to identify the most influential figures in Malaysian politics during election periods. This method allows us to map the network of political actors and their relationships, providing insights into the power dynamics at play. Subsequently, we will apply topic modeling techniques to analyze the discourse generated by these key figures, focusing on their primary talking points, policy positions, and rhetorical strategies.

Through this study, we aim to provide a comprehensive understanding of how Malaysian political figures utilize social media to shape public opinion and influence election outcomes. Our findings will contribute to the broader scholarly discussion on the intersection of social media, politics, and public discourse in diverse societies while offering insights that may be valuable for policymakers, journalists, and citizens seeking to navigate Malaysia's complex political landscape.

The rest of the paper is organized as follows. The Related Work section provides a comprehensive background on the use of social media in election studies and the detecting of influential actors from social networks. In the Data Collection section, we provide our approach to data collection and processing. Next, we discuss our methodology, where we present our CFSA and Topic Modelling evaluation framework. The Results and Discussion section contains our analysis as we identify the key focal structure for the Malaysian Election. We conclude with the findings and future work in the Conclusions and Future Work section.

II. Related work

This part of our study examines two critical areas: the role of social media in election studies and the analysis of influential structures in social networks. The first subsection explores how researchers use social media data to understand public opinion and electoral trends, while the second investigates methods for identifying influential actors in digital communities, particularly within the blogosphere. These areas provide insight into the intersection of digital platforms, public discourse, and political processes in contemporary society.

A. Using Social Media for Election Study

The digital age has transformed electoral research, with social media emerging as a crucial instrument for studying political processes. These platforms provide researchers with an unprecedented wealth of real-time data, enabling in-depth analysis of public opinion, electoral trends, and political communication. Investigators have harnessed sophisticated computational methods, such as sentiment analysis, content mining, and advanced machine learning algorithms, to extract valuable insights from popular social media sites, including Twitter, Facebook, and Instagram, during election campaigns. This approach has revolutionized the way researchers assess voter sentiment, monitor the dissemination of political narratives, and

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investigate the complex relationship between online political engagement and actual voting patterns. By leveraging these digital footprints, scholars can now paint a more comprehensive picture of the electoral landscape, offering nuanced perspectives on how public discourse in the virtual realm influences and reflects real-world political outcomes.

Recent studies have demonstrated the diverse applications of social media analysis in electoral research. For instance, Balakrishnan et al. [3] examined online communication patterns during Malaysia's 2018 General Election, utilizing sentiment and content analyses on tweets. Their study employed machine learning models such as Naive Bayes and Support Vector Machine, finding that Naive Bayes combined with Word2Vec vectorization was most effective for sentiment analysis. In a broader context, Rita, António, and Afonso investigated social media's influence on voting decisions during the 2019 UK General Elections, analyzing tweet sentiment related to major political parties and candidates. Their research cautioned against using social media sentiment as a reliable predictor of election outcomes [4]. Similarly, Belcastro et al. conducted an in-depth analysis of voter behavior on Twitter during the 2020 US presidential election campaign, applying topic discovery, opinion mining, and emotion analysis techniques to determine users' political orientations and the emotional underpinnings of their support [5]. These studies collectively highlight the potential of social media as a rich data source for understanding electoral dynamics and voter behavior while also underscoring the complexities and limitations of such analyses in predicting election results or fully capturing the nuances of public opinion.

B. *Influential Structures in Social Networks*

In the field of social network analysis, several studies have been conducted. Agarwal et al. explain the impact of blogs and the blogosphere on online discourse and public opinion in the Web 2.0 era. It highlights how blogs have created virtual communities for sharing thoughts and debates, influencing various sectors, from business to politics. The research focuses on identifying influential bloggers in community blogs, drawing parallels with real-world "influentials" whose opinions are highly valued. Jiang. et. el. developed methods for quantifying blogger influence by analyzing community reactions to their posts, addressing challenges such as defining influence metrics and creating adaptable models where authors propose an algorithm (iFinder) to compute influence scores and develop a prototype tool for real-world blog analysis [6].

Another research from 2008 suggests that blogs have become a significant platform for information dissemination and social interaction in the digital age. This study expands on the previous research by examining the broader impact of blogs within the Web 2.0 ecosystem. It highlights how blogs, characterized by their reverse chronological order of entries and interactive comment sections, have lowered the barriers to publication and fostered global collaboration. The research emphasizes that blogs are not just isolated platforms but part of a larger shift in Internet culture, moving from the passive consumption model of Web 1.0 to the active contribution model of Web 2.0. This transformation has led to the emergence of collective wisdom and open-source intelligence as users collaborate and edit content on a mass scale. The study points out that this new paradigm of online interaction provides rich opportunities for research into the structural and temporal dynamics of blog communities and other social networking services [7].

Building upon the previous research, another study further explores the transformative impact of Web 2.0 and blogs on information dissemination and social interaction. It emphasizes how shifting from passive consumption to active content creation has fundamentally altered the digital landscape. The study focuses on the blogosphere as a key component of this new paradigm, highlighting its role in forming virtual communities and influencing various sectors, from business to politics. A significant contribution of this study is its exploration of methodologies for identifying influential bloggers within these digital communities. This aspect is particularly crucial as it addresses the growing need to understand and leverage online influence in an era where social media significantly shapes public opinion and consumer behavior [8].

Other social media researcher delves into the darker side of digital platforms, focusing on the spread of misinformation, particularly during the COVID-19 pandemic. Their study introduces a novel manual node-based design for filtering large datasets, addressing limitations in AI-based detection methods. By analyzing a curated dataset, including YouTube comments, the research provides insights into the themes and dynamics of COVID-19 misinformation. Their work helps examine how the anonymity and reach of social media facilitate deviant behaviors and the rapid dissemination of false information. That highlights the unique challenges posed by the COVID-19 'infodemic', where misinformation spreads faster than factual content, driven by various motives from monetization to political agendas [9].

III. Data Collection

This study focuses on the 2022 Malaysian general election, a pivotal moment in recent political history. We chose this election due to its significance in Malaysia's democratic process and the heightened social media activity surrounding it. The 15th Malaysian general election, held on November 19, 2022, marked a crucial juncture in the nation's politics [10], coming after a period of political instability and amid ongoing economic challenges.

To capture the digital discourse around this election, we collected data from Instagram, one of the most popular social media platforms in Malaysia. Instagram was selected for its widespread use among Malaysian voters, particularly younger demographics, and its capacity for both visual and textual political communication. We identified and used the following hashtags to collect relevant data: #UndiHarapan, #KitaBoleh, #PH, #Election2022, #Malaysia, #AnwarIbrahim, #PakatanHarapan, #GE15, #KelasDemokrasi, #PRU15, and #MalaysiaMemilih.

These hashtags were chosen based on their popularity and relevance to the election, political parties, key figures, and general election-related discourse in Malaysia. For data collection, we employed the APIFY scraper tool. Using APIFY, we gathered a comprehensive dataset of 53,116 Instagram posts that included these hashtags.

We focused on the 2022 general election and utilized this data collection method. Our research aims to provide insights into the most recent major political event in Malaysia, offering a timely and relevant analysis of the country's evolving political landscape as reflected through social media engagement.

IV. Methodology

In this section, we will explain the detailed methodology to analyze Instagram discourse during the 2022 Malaysian general election. First, we apply Contextual Focal Structure Analysis (CFSA) [11] to identify influential user groups within the mentioned network. This is followed by a detailed CFSA analysis of our Instagram dataset. Finally, we use topic modeling to understand the key themes discussed within these focal structures, providing a comprehensive view of the election's social media landscape.

A. Background of CFSA

The Contextual Focal Structure Analysis (CFSA) model represents a advancement in social network analysis, particularly for understanding complex online interactions. CFSA builds upon traditional network analysis methods by incorporating contextual information alongside user interactions, allowing for a more nuanced understanding of network dynamics. CFSA helps in detecting key sets of actors in a network that collectively exert the most influence over the network. In other words, such key actors are responsible for large-scale and complex social processes such as social movements, protests, coordinating information campaigns, etc. Unlike simpler models that focus solely on user-user connections, CFSA integrates multiple layers of information, such as shared topics or hashtags, to provide a richer representation of social interactions. This multi-layered approach enables researchers to uncover hidden connections, identify influential sets of users sharing similar contexts, and gain deeper insights into information flow within networks. CFSA further ranks the key sets of actors based on their influence over the network. The model's ability to handle complex, context-rich data makes it particularly valuable for analyzing intricate social and political landscapes where diverse narratives and interests intersect.

In the context of our research on the 2022 Malaysian general election, CFSA offers several key advantages that justify its application. Malaysia's political landscape is characterized by a complex interplay of ethnic, religious, and economic factors, which are reflected in online discourse. By employing CFSA, we aim to capture and analyze these diverse political narratives as they manifest on social media, particularly Instagram. The model's capability to identify contextual focal structures allows us to pinpoint not just individual influencers but groups of users who collectively shape political discourse. This is crucial for understanding the dynamics of Malaysia's coalition-based political system and how it translates into online engagement. Furthermore, given concerns about media censorship in Malaysia, CFSA's ability to map information flow provides valuable insights into how political messages spread and gain traction on social platforms. Ultimately, by applying CFSA to our dataset of Instagram posts and user interactions, we aim to uncover the key drivers of political discourse during the election period, understand the formation of opinion clusters, and assess the impact of social media on political engagement in Malaysia's evolving democratic landscape.

B. CFSA Analysis

Building upon our data collection from Instagram posts related to the 2022 Malaysian general election, we proceeded to analyze the data using a modified CFSA approach. This method was adapted to focus solely on user mentions, creating a network based on how users interacted with each other in the context of election-related discussions [12].

Our analysis began with compiling a list of users linked to the election-related hashtags. We implemented queries to collect bulk user data, including profiles, number of posts, likes, followers, geographic information, usernames, mentions, web links, and biographies. This comprehensive dataset provided the foundation for constructing the user mentioned network essential to our research objectives [6].

Utilizing this collected data, we generated a co-occurrence users' network (Figure 1) based on mentions. This network represented the interconnections between users, forming the primary layer of our analysis. Users who mentioned each other in their posts were considered linked, creating a web of interactions that reflected the discourse around the Malaysian general election.

The next phase involved integrating this user-mentioned network into our modified CFSA model. This model accepted users and the links between them based on mentions, representing a coupling matrix. The outcome of this step included the smallest possible contextual focal structure sets, comprising influential users within different communities who were frequently mentioned or who mentioned others in election-related posts. Through manual analysis, we identified the Contextualized Focal Structure sets, focusing on attributes such as size, number of users, and number of edges in each set.

By adopting the CFSA methodology to focus exclusively on user mentions, we identified key influencers and interaction patterns that shaped the online conversation around the 2022 Malaysian general election. This approach allowed us to uncover the complex network of user interactions, providing valuable insights into the dynamics of political discourse on social media during this critical period in Malaysian politics.

C. Topic Analysis

In the final phase of our methodology, we conducted the topic analysis to uncover the primary themes discussed within the identified focal structures. We employed Latent Dirichlet Allocation (LDA), a widely-used topic modeling technique, to extract and analyze the most frequent topics from the textual content associated with each focal structure [13].

LDA is a probabilistic model that assumes each document is a mixture of topics, and each topic is a mixture of words. This approach allows us to discover underlying themes in large collections of text data, making it ideal for analyzing the diverse discussions within our Instagram dataset.

To ensure the reliability and interpretability of our topic analysis, we performed a robustness check by calculating two key metrics: Perplexity Score and Coherence Score. We achieved a perplexity score of 8.07. Perplexity measures how well the model predicts a sample. A lower score indicates better generalization of the model to unseen data, suggesting our LDA model effectively captures the underlying topic structure of the texts. Our model yielded a coherence value of 0.59. Coherence measures the degree of semantic similarity between high-scoring words in each topic. A higher coherence value indicates more interpretable and semantically coherent topics, implying that our identified topics are meaningful and distinct.

These metrics demonstrate the quality and reliability of our topic modeling results, providing a solid foundation for interpreting the key themes and discussions within the focal structures of Malaysia's election-related Instagram discourse.

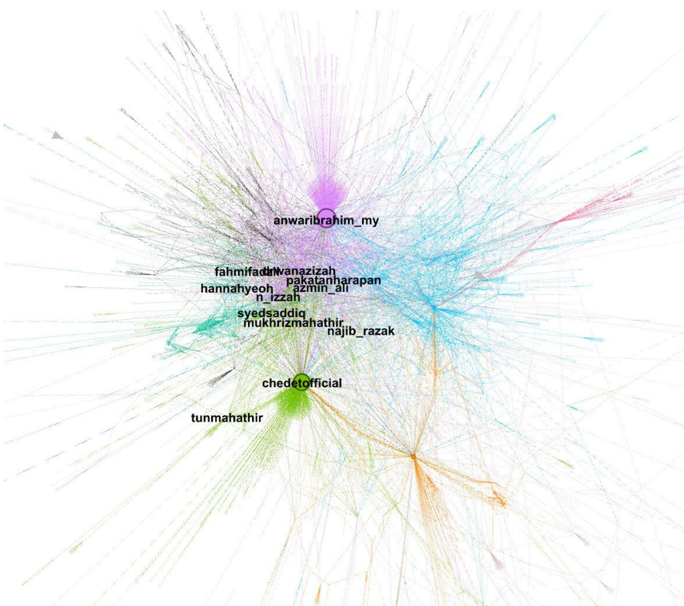


Figure 1. User Mention Network - Highlighting most mentioned user

V. Results & Discussion

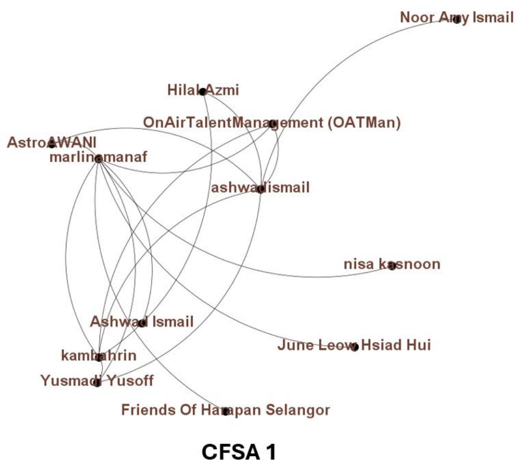
Among 11 focal structures, we pick CFSA 1 in Figure 2, as it is the most influential structure as suggested by the CFSA methodology. CFSA 1 unveils a network of interconnected individuals and entities that played significant roles in shaping the online discourse during the 2022 Malaysian general election. This network is primarily composed of two distinct yet interrelated groups: journalists/media houses and politicians/political parties. The media group includes prominent figures such as Hilal Azmi, Kambahrin, Ashwad Ismail, Marlinamanaf, and Nisa Kasnoon, alongside media organizations like Astro AWANI and OnAirTalentManagement (OATMan). These entities were instrumental in covering and discussing the election. On the political front, the network features June Leow Hsiad Hui, Friends Of Harapan Selangor, and Yusmadi Yusoff, who represent key political actors and party-affiliated organizations.

The visualization of this network provides crucial insights into the flow of information and influence within this group during the election period. It highlights the intricate connections between media personalities and political figures, demonstrating the complex interplay between journalism and politics in shaping public opinion. This close interaction suggests that media played a significant role in crafting and disseminating political narratives throughout the election cycle.

By identifying these key actors and their relationships, the CFSA result offers a nuanced understanding of the Malaysian election discourse. It not only pinpoints the most influential personalities shaping online conversations but also reveals potential pathways of information dissemination. The frequent keywords associated with this network, such as "marlinamanaf," "luqmanhariz," "Malaysia chooses," "KamiAWANI," "MalaysiaMemilih," and "Anwar Ibrahim," provide valuable context about the dominant topics and figures in the discourse. The close interconnection between media professionals and politicians underscores a blurring of lines between these sectors, raising questions about media independence and the framing of political narratives. While the presence of diverse media entities such as Astro AWANI and OnAirTalentManagement suggests a varied media landscape offering multiple perspectives on the election, the political representation appears imbalanced. The explicit mention of "Friends Of Harapan Selangor" without strong representation from other political parties indicates a potential disparity in online presence or influence among different political factions during this crucial period. Our results revealed that media outlets and political parties generally employed dist nct approaches to framing narratives. However, in some instances, we observed overlaps in their framing strategies. This network structure not only highlights the central role of media in shaping public opinion during elections but also points to potential challenges in maintaining a balanced and diverse political discourse in the Malaysian online sphere. The presence of both media and political entities in a single network underscores the cross-sector influence at play during the election. This amalgamation suggests a symbiotic relationship between media coverage and political messaging, likely influencing how the public perceives and engages with election-related information.

This dataset was collected with focused hashtags, and because of that, for every focal structure analysis, we obtained a result that was primarily related to Malaysian political entities or different media entities. In a few cases, we observed Chinese language newspapers like "Guang Ming Daily" and "China Press".

This comprehensive CFSA result enables a more sophisti-



Frequent Keywords in Topics
marlinamanaf, luqmanhariz, Malaysia chooses, KamiAWANI, MalaysiaMemilih, Anwar Ibrahim

Breakdown of CFSA 1	
Journalist/Media House	Hilal Azmi, Kambahrin, Ashwad Ismail, Marlinamanaf, Nisa Kasnoon, Astro AWANI, OnAirTalentManagement (OATMan)
Politician/Political Party	June Leow Hsiad Hui, Friends Of Harapan Selangor, Yusmadi Yusoff

Figure 2. CFSA 1 set (among 11 focal structures) with breakdown and Frequent Keywords obtained by LDA

cated analysis of information dissemination, narrative formation, and influence distribution in the online discussions surrounding the Malaysian general election. Since CFSA is a combination of FSA analysis and contextual analysis, these insights are invaluable for understanding the dynamics of political communication and the formation of public opinion in the era of social media, especially during critical democratic processes. By mapping these key actors and their interconnections, we gain a deeper appreciation of how digital platforms shape political discourse and potentially influence electoral outcomes in contemporary Malaysia.

VI. Conclusion and Future Work

This research provides valuable insights into the dynamics of political discourse on social media during the 2022 Malaysian general election. By employing CFSA and topic modeling on a substantial dataset of Instagram posts, we have uncovered complex networks of influence and information flow that shaped public opinion and political narratives.

Our findings highlight the significant role of social media, particularly Instagram, in modern political communication. The identified focal structures reveal an intricate interplay between journalists, media houses, politicians, and political parties, demonstrating how digital platforms have become crucial for political engagement and information dissemination. The convergence of traditional media figures and political actors in these online spaces underscores the evolving nature of political discourse in the digital age.

The study also sheds light on the key topics and themes that resonated with Malaysian voters during the election period, providing a nuanced understanding of the issues that drove public engagement. This insight is crucial for comprehending the factors influencing voter behavior and political participation in contemporary Malaysia. Our methodology offers a robust approach to analyzing complex digital interactions in political contexts, contributing to the broader field of digital democracy studies. By combining network analysis with content analysis, we have demonstrated an effective approach to decoding the multifaceted nature of online political communication.

Future research could expand on this study in several key directions. A cross-platform and multi-modal analysis incorporating data from platforms like TikTok and Instagram with images and videos would provide a more comprehensive view of Malaysia's digital political landscape, allowing for comparisons of discourse patterns across different social media environments. To understand the political parties' strategic use of multimodal platforms like Instagram and TikTok, we intend to expand our study as well. Additionally, investigating the correlation between social media engagement patterns and voting outcomes would offer valuable insights into the real-world impact of online political discussions. Such research could help quantify the influence of social media on electoral behavior and further our understanding of how digital platforms shape modern democratic processes.

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Examining the Impact of Toxicity on Community Structure in Social Networks

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***Abstract*— Social media platforms, such as X continue to increase efforts to reduce harmful content, such as hate speech due to their impact on communities. The increase in harmful content was even more noticeable in 2020 with COVID-19 topics. This research systematically examines the impact of toxicity on the dynamics of communities on X, such as pro-vaccine, anti-vaccine COVID-19. Toxicity score calculated and social network analysis was performed to extract communities. These factors were co-analyzed to understand if the communities become more cohesive or more fractured over time with varying toxicity levels using Granger causality test. Our results demonstrate that in the pro-vaccine dataset, toxicity has a more substantial effect on community dynamics by fracturing communities as toxicity increases, whereas in the anti-vaccine dataset toxicity does not affect the community dynamics as much. These results have implications for how social media platforms can better moderate content and reduce toxicity within communities.**

Keywords- Toxicity; Community dynamics; Social network; Granger causality; Network analysis; Community structure.

I. INTRODUCTION

Social media platforms like Facebook and X (formerly Twitter) connect users globally but also facilitate the sharing of toxic content, which includes impolite or disrespectful language. Nockleby defines the hate speech as "any communication that disparages a person or a group on the basis of some characteristic such as race, color, ethnicity, gender, sexual orientation, nationality, religion, or other characteristic" [1]. Such content can harm community health and engagement [2]. Platforms have guidelines to manage toxic content due to its significant impact [3] [4]. With 48% of US adults getting news from social media [5]. Sometimes, information on social media can lead to real-life events, and vice versa [6]. Communities form and dissolve for various reasons, such as friends and family sharing content or strangers engaging with unfamiliar posts. Mixed communities blend these dynamics, creating networks of communication [7]. Users can expand communities by retweeting, mentioning, following, liking, or sharing content. However, this can evoke emotions in the users [8] . disagreements may lead to unfollowing and stopping the sharing of previously shared content [9], [10].

This research examines the impact of toxicity on community dynamics for COVID-19 vaccine content on X. A longitudinal analysis of anti- and pro-vaccine hashtags investigates differences between these communities. The two primary research questions (RQs) addressed are: **RQ1:** What is the role of toxicity in community dynamics? **RQ2:** Does toxic speech fracture a community or make it more cohesive?

Creating Sankey diagrams for both the anti- and pro-vaccine datasets, color-coded by average toxicity score, reveals toxicity dynamics at the community level. A Granger Causality test analyzed the impact of toxicity on community structure and average nodes. Results show that in the pro-vaccine dataset, increased toxicity significantly affects and fractures communities, while in the anti-vaccine dataset, toxicity has less impact. This difference is due to greater opinion diversity in the pro-vaccine data compared to the anti-vaccine data. This research explores how toxicity affects pro-vaccine and anti-vaccine communities, offering insights for improving online discourse and community management. It helps policymakers understand the behavioral differences between antagonistic and supportive communities.

In the following section 2 provides a background on existing research in toxicity and polarization, section 3 describes the details of our methodology. In Section 4, we present results and findings. Finally, section 5 summarizes our findings and discusses potential future work.

II. LITERATURE REVIEW

We review literature on hate speech followed by computational studies on community dynamics.

A. Hate Speech and Community Polarization

Toxic or hateful speech is common online and significantly impacts social network dynamics, particularly by shaping online communities and influencing information flow, especially when targeted at perceived out-groups [11]. The study [12] found that hateful posts spread faster and wider than non-hateful ones, and posts with picture attachments performed best, suggesting viral memes aid in spreading information. Authors in [13] used three measurements of graph structure to study the relationship between toxicity and the interconnectedness of X communities: connected components, modularity, and overall embeddedness.

Researchers use various techniques to measure and analyze social network structure and polarization. A study used social network analysis and natural language processing to study how political discussions on social media in Japan lead to echo chambers and user polarization [14]. Deitrick and Hu improved community detection in four X networks by integrating sentiment analysis and adding features to tweets [15]. In [16], the authors developed an index to evaluate

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network polarization and used it to reduce polarization by promoting content on controversial subjects.

B. Change in Response to Events

Online communities, like offline ones, are constantly evolving and can shift in response to external factors that provoke strong emotions. In [17], the X social network was studied before and after the 2015 Charlie Hebdo attack, revealing that users became more emotional and negative. In [18], polarization in a Swiss social network during the 2011 federal elections was analyzed using time series and network measures, showing that polarization peaked before the election and returned to normal afterward. Authors in [19] analyzed communities and influential users on X in Slovenia during recent political changes and the Covid-19 pandemic, finding increased political polarization. In [20], the study of blog posts by female bloggers on women's rights focused on broker and bridge nodes and their impact on information flow.

III. METHODOLOGY

This section discusses the research methodology used to study coordination and dynamic of social media, through various types of networks.

A. Data Collection

In this study, we focused on two different datasets to perform community dynamics analysis that were collected using the X academic API to collect tweets related to COVID-19 from January 1, 2020, to June 30, 2021. The data was collected for various sets of hashtags that included subjects related to COVID-19. The collected hashtags were classified into anti-hashtags and pro-hashtags categories regarding vaccination. Some examples of hashtags collected for the anti-vaccine dataset include #VaccineKill, #nocovidvaccine, and #NoVaccineForMe, etc. For the pro-vaccine dataset, some hashtags include #vaccinecure, #getthevaccine, etc.

B. Toxicity Detection

Toxicity scores for each tweet in the datasets were computed using Detoxify, a model created by Unitary [21]. This model uses a Convolutional Neural Network (CNN) trained with word vector inputs to assess whether text is perceived as "toxic." The Detoxify API returns a probability score between 0 and 1, with higher values indicating a greater likelihood of toxicity. A threshold of 0.531 was set for identifying toxic tweets, balancing precision and recall as established by [13]. Texts with toxicity scores above 0.5 are labeled as 'toxic'.

C. Community Dynamics

The data was processed into a daily time series for analysis using NetworkX algorithms, such as the determining modularity and clustering coefficient, number of communities, and nodes. Modularity is a proposed division of that network into communities. It evaluates the quality of community division based on the presence of numerous edges within communities and the few between them [22], and is calculated according to Equation (1).

$$Q = \sum_{c=1}^{n} \left[\frac{L_c}{m} - \gamma \left(\frac{K_c}{2m}\right)^2\right] \tag{1}$$

Another characteristic of a network is the clustering coefficient, which measures the extent to which nodes within a graph tend to form clusters. A high clustering coefficient suggests that nodes are closely connected within clusters, with many connections among neighboring nodes. Conversely, a low clustering coefficient indicates a more dispersed network structure. Equation (2) calculates the clustering coefficient.

$$C_i = \frac{2e_i}{n_i(n_i-1)} \tag{2}$$

Calculated statistics included the minimum toxicity score, maximum toxicity score, maximum toxicity minus minimum toxicity score, toxicity mean, toxicity standard deviation, toxicity quantile 1, toxicity quantile 2 and toxicity quantile 3.

D. The Granger Causality

The Granger Causality test was used to predict one time series from another. A Python script facilitated this test, but before it could be conducted, the data were checked for stationarity using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The Granger Causality test requires both time series to be stationary; otherwise, the data were transformed to achieve stationarity. Two tests for both the anti- and pro-vaccine data were run for the daily data for the Granger Causality test. The first test consisted of the average toxicity score of the communities and the number of communities. The second test consisted of the average toxicity score and the average nodes of the communities.

E. Sankey Diagrams and Five Point Statistical Summary

Sankey diagrams illustrate node flow within communities and transitions between them over time. The Jaccard Similarity Index (Equation 3) measures the data similarity, with scores ranging from 0 to 1, where higher scores indicate greater similarity [23].

$$J(A,B) = |A \cap B| / |A \cup B| \tag{3}$$

The data from the statistical analysis was used to develop the Sankey diagrams and five-point statistical summary. Ten dates were randomly selected for the anti-vaccine and pro-vaccine datasets. The largest community was used for the analysis if the sample date had more than one community with greater than two nodes. The date selected in the sample and the following three days were used for the data to create the Sankey diagrams to look at the community dynamics.

The five-point statistical summary was calculated for the communities for the sample data for anti- and pro-vaccine datasets. This included the minimum toxicity, maximum toxicity, and toxicity quantiles 1, 2 (median), and 3. The five-point statistical summary provides insight into toxicity score distribution within communities. Toxicity quantile 2 shows us the median for the data, while toxicity quantiles 1 and 3 show the spread of the toxicity scores, and the minimum and maximum toxicity create the data range.

IV. RESULTS AND FINDINGS

Correlation analysis examined weekly modularity scores, clustering coefficients, and average toxicity scores in anti- and pro-vaccine datasets. Sankey diagrams and Granger causality tests were also applied.

A. *Modularity and Toxicity*

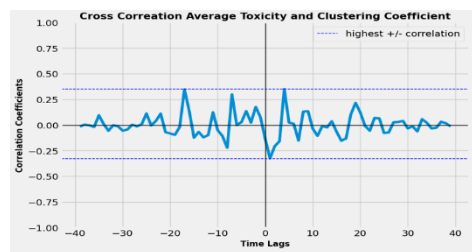
Analysis was conducted for several datasets by looking at the daily modularity scores for the user communication network (i.e., retweets and mentions) combined with the average toxicity scores, to see if toxicity is a factor in causing a community to fracture. The higher the modularity score of a network, the more modular (i.e., cohesive/well-knit) the community is. The lower the modularity score of a network, the less modular (i.e., loosely-knit) the community is. When there is a spike in toxicity in the time series, and the modularity score dips within a period of a few days, toxicity could be the cause of the fracturing of the community. A dip in modularity is noticed within a few days, because there can be a lag in the time series. The daily time series for several months of the datasets shows spikes in the toxicity mean score and dips in the modularity score the same day or day after the toxicity mean spikes. This can indicate that as toxicity rises over the network, it causes the modularity to drop, which is a sign of community fracturing.

Occurrences of significant toxicity spikes and subsequent modularity dips were observed at various points in time across the different datasets. For instance, in the anti-vaccine dataset, such occurrences were noted in January, June, and September of 2020, as well as in November 2020. In March 2021, a notable increase in toxicity was followed by a significant decrease in modularity, indicating a strong indication of community fragmentation due to increased toxicity. Similarly, even though the pro-vaccine dataset exhibited less toxicity overall—notably in January, August, October, and November 2020—the pro-vaccine results still showed frequent spikes in toxicity and corresponding dips in modularity; namely, the pro-vaccine dataset experienced mild but frequent spikes in toxicity and modularity dips, primarily occurring in April and June 2020. These findings show toxicity within a community affects modularity and has an impact on community fragmentation for both datasets.

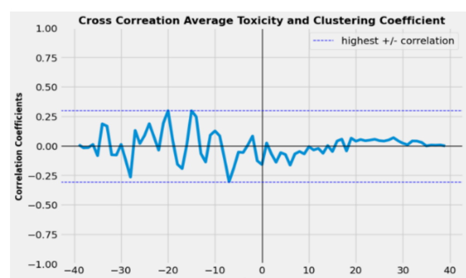
B. *Clustering Coefficient and Toxicity*

The analysis examined from the multiple datasets the weekly clustering coefficient of a user communication network alongside the average toxicity scores. This investigation aimed to detect whether toxicity plays a role in community fragmentation. A high clustering coefficient indicates dense connections among nodes within clusters, implying strong cohesion and frequent interactions among neighboring nodes. In contrast, a low clustering coefficient signifies a more scattered network structure, suggesting weaker ties and less frequent interactions among nodes.

Figure 1 illustrates the cross-correlation between toxicity scores and clustering coefficients for various time lags, aiming to identify the time lag at which the highest correlation between toxicity and clustering coefficient occurs. In Figure 1-A, showing the anti-vaccine dataset, a correlation is -0.23 with an 8-week lag. And Figure 1-B, representing the pro-vaccine dataset, a correlation of -0.34 is observed with a 7-week lag. This temporal aspect enriches the analysis, revealing how toxicity over time affects online community cohesion. Negative correlations (-0.23 and -0.34) indicate that, as toxicity increases, communities tend to become more fragmented. A decrease in the clustering coefficient signifies weaker member connections and reduced interaction frequency. For the anti-vaccine Figure 1-A, the correlation of -0.23 with an 8-week lag suggests that there is a modest negative association between toxicity levels and community cohesion. This means that, as toxicity increases, the community tends to become less cohesive, but this effect is observed with an 8-week delay. In contrast, in the pro-vaccine dataset Figure 1-B, the correlation of -0.34 with a 7-week lag indicates a slightly stronger negative relationship between toxicity and community cohesion compared to the anti-vaccine dataset. This implies that increases in toxicity levels are associated with more immediate and stronger decreases in community cohesion in pro-vaccine discussions, with a lag of around 7 weeks. The findings help us understand how toxicity affects the fundamental structure and behavior of online communities.



A. Cross correlation for Anti vaccine



B. Cross correlation for Pro vaccine

Figure 1. Cross correlation between toxicity and clustering coefficient.

C. *Sankey Diagrams*

Sankey diagrams were created to deeply investigate the dataset's community dynamics and to look specifically at the community dynamics for the anti-vaccine and pro-vaccine datasets. These diagrams help visualize what happens on the first day of a time series to the communities with an average

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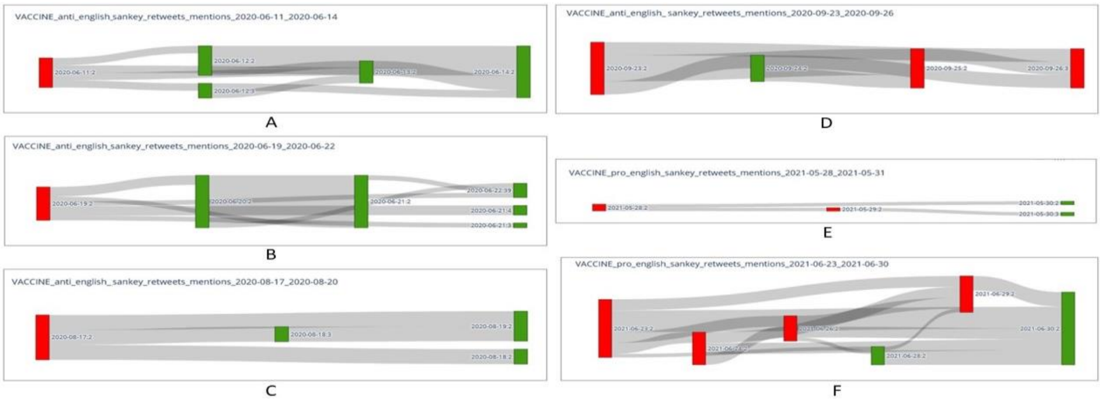

Figure 2. Community Sankey flows for different time periods.

toxicity score of greater than 0.5. Community 2020-06-11 started with two nodes that split into four different communities in the time series (Figure 2-A). The first node transitioned from the community with ID 2 on 2020-06-11 (2020-06-11:2) to the community with ID 2 on 2020-06-12 (2020-06-12:2). And the second node went to the 2020-06-12:3, 2020-06-13:2, and 2020-06-14:3 communities. These nodes' changes in community reflect the fragmentation of the original community. The tweet/retweet was the same for all nodes of the 2020-06-11:2 community, giving it the same score across the five-point statistical summary and for community 2020-06-14:2.

For the 2020-06-12:2 community, toxicity scores ranged from 0.0004 to 0.9894. In the 2020-06-12:3 community, scores ranged from 0.0007 to 0.0012. The 2020-06-14:2 community had scores ranging from 0.0004 to 0.8495. Additionally, community 2020-06-19:2 saw four out of twenty-three nodes flow into five different communities over the time series (Figure 2-B). On 2020-09-10:2, all nodes in the community retweeted the same tweet, resulting in a median toxicity score of 0.7142, with uniform quantiles and minimal variability. The 2020-06-21:2 community had a toxicity range from 0.0004 to 0.1646. On 2020-08-17:2, a community began with a median toxicity score of 0.8629, and two of its four nodes later moved to non-toxic communities (Figure 2-C). Communities 2020-08-17:2, 2020-08-18:3, and 2020-08-19:2 had identical toxicity scores due to the same retweet. The non-toxic community 2020-08-18:2 had toxicity scores ranging from 0.0004 to 0.2999. In the 2020-09-23:2 community, two nodes flowed to other communities; one node entered all subsequent communities but remained toxic, while the other moved directly to the 2020-09-26:3 community (Figure 2-D). Three additional days were analyzed, and no further connections from the 2020-09-26:3 community were found. Only the 2020-09-24:2 community had consistent five-point statistical scores. The 2020-09-23:2 community had toxicity scores ranging from 0.8765 to 0.9689, the 2020-09-25:2 community had scores between 0.7455 and 0.9842, and the 2020-09-26:3 community ranged from 0.3512 to 0.9516.

The pro-vaccine results were similar to the anti-vaccine sample dataset. In the first pro-vaccine sample dataset, the community 2021-05-28:2 started with eight nodes and then split into two different communities (see Figure 2-E). Two nodes went to other communities, while one node went straight to the non-toxic community. Two communities, 2021-05-28:2 and 2021-05-29:2, had the same score for the five-point statistical analysis. The other two communities were skewed. The 2021-05-30:2 community had a minimum toxicity score of 0.0178 and maximum toxicity score of 0.0433. The 2020-05-30:3 community had a minimum and maximum toxicity score of 0.0004 and 0.0993, respectively.

For the 2020-06-23:2 community, additional days were added to see if the toxic communities had more flowed additions. After analyzing the additional days, all the toxic communities ended in a non-toxic community for the time series (see Figure 2-F). Three of the six communities, 2021-06-24:3, 2021-06-26:2, and 2021-06-29:2, had the same score for the five-point statistical analysis. The other three communities were skewed. The 2021-06-23:2 community had a minimum toxicity score of 0.0004 and maximum toxicity score of 0.6074. The 2021-06-28:2 community had a minimum and maximum toxicity scores are 0.0004 and 0.9832, respectively. The 2021-06-30:2 community had a minimum toxicity score of 0.0004 and maximum toxicity score of 0.6074.

Overall, our analyses indicate seven out of the ten anti-vaccine communities with nodes that had connections to other communities in the time series flowed into non-toxic communities by the end of the time series for each sample. For the pro-vaccine communities, eight of the ten communities' nodes ended flowing into in non-toxic communities. This Sankey diagram analysis in Figure 2 shows that toxicity can cause the fracturing of a community.

D. Granger Causality Test

The Granger Causality test was conducted on both the anti-vaccine and pro-vaccine datasets to explore the relationship between the communities' average toxicity scores and characteristics/values, such as number of communities and number of nodes.

Initially, for the anti-vaccine dataset, the first test was between the average toxicity score of the communities and the number of communities. The ADF test was run on the toxicity and community column data, and this test was performed to assess data stationarity. For data to be considered stationary, the p-value must be less than 0.05. The p-value for the toxicity and community were 3.4056e-5 and 0.0147, respectively. So, the data series was stationary. Since the data passed the ADF test, the next step was to conduct the KPSS test to verify if the data exhibited stationarity. For the data to be stationary, the *p*-value must be greater than 0.05. The *p*-value for the toxicity and community were 0.015392 and 0.015392. So, in this case, the data series were not stationary.

Since the data did not pass the KPSS as stationary for the time series, we addressed this issue by transforming the data through differencing. After performing the differencing process, we conducted the ADF and KPSS tests again, confirming that all data series now exhibited stationarity. With both the ADF and KPSS tests passed, we proceeded to conduct the Granger Causality test using four lags. In the Granger Causality test, for either the toxicity value or the community value to Granger-cause the other variable, the p-value must be less than 0.05. The results indicated that toxicity did not Granger-cause the community values, as evidenced by p-values of 0.8127, 0.9343, 0.9898, and 0.9794 for lags 1 to 4, respectively. Similarly, the community factor did not Granger-cause toxicity for all four lags, with p-values of 0.4724, 0.7906, 0.9101, and 0.9238.

For the pro-vaccine data, the ADF test was run on the toxicity column data and the number of community column data. The toxicity data series were stationary, but the community data were not, with p-values 2.0483e-13 and 0.795, respectively. The next test performed to see if the data was stationary was the KPSS test; the toxicity, with a p-value 0.100, was stationary, but the community, with p-value 0.010, data series was not stationary. Since the community data did not pass the KPSS as stationary for the time series, the data was transformed by differencing the time series data. After the difference was performed, the ADF and KPSS tests were rerun, and all the data series passed as stationary. The Granger Causality test was performed using four lags. The outcome of the data was that toxicity does not Granger-cause the community values, and that the community values do not Granger-cause the toxicity for all four lags for toxicity and community with the p-values that are way greater than 0.05 in both cases for 4 different lags.

The second test conducted was the average toxicity score, and the average nodes of the communities.

The ADF test was run on data for the anti-vaccine dataset. The average toxicity and average nodes data series were stationary with the p-value of 3.4056e-5 and 0.049 respectively. Since the data passed the ADF test, the next test performed was KPSS to see if the data was stationary. The toxicity and average nodes data series were not stationary with p-value 0.01. Since the data did not pass the KPSS as stationary for the time series, the data was transformed by differencing the time series data. After the difference was performed, the ADF and KPSS tests were rerun, and all the data series passed as stationary. The Granger Causality test was performed using four lags. The outcome of the data shows toxicity does not Granger-cause the average nodes, as observed by p-values 0.81,0.93,0.98,0.97 for four lags.

For the pro-vaccine data, the ADF and KPSS tests were run on the toxicity column data and the average nodes column data. All the data series passed as stationary, expect KPSS for the average nodes. After the difference was performed, the ADF and KPSS tests were rerun, and all the data series passed as stationary. The Granger Causality test was performed using four lags. The outcome of the data was that toxicity does not Granger-cause for the average toxicity lag one (p-value 0.495) and four (p-value 0.07), but it does Granger-cause on lag two (p-value 0.033) and three (p-value 0.036). Toxicity does affect the average number of nodes in a community. Lag two has the strongest effect since its p-value is lower than lag three. This demonstrates that as toxicity increases, it affects the average nodes in a community with a lag, which is to be expected. One shouldn't see Granger Cause at the same time. When looking at how the average nodes affect toxicity, the lag two, three, and four all Granger-caused. Out of all the lags, the strongest one was lag two.

V. Conclusion and Future Works

For the anti- and pro-vaccine datasets, several months show that, as the toxicity mean score rises or spikes, the modularity toxicity score decreases within a few days. When the modularity score is high and then decreases after the rise or spike of toxicity, the community becomes less tight-knit, and this shows toxic that an increase in toxicity can cause the community to fracture. Similarly, the clustering coefficient exhibits a similar trend, with an increase in toxicity corresponding to a decrease in the clustering coefficient, signifying community fracture. In the pro-vaccine dataset, an increase in toxicity leads to earlier and higher fragmentation compared to the anti-vaccine dataset. When examining community dynamics, communities starting with a toxicity score above 0.5 tend to fracture. These toxic communities often break into smaller groups, including primarily non-toxic ones. Even when members join other toxic groups, their new toxicity scores are lower than the original. Thus, a less toxic community is preferable to a highly toxic one. When the anti- and pro-vaccine sample datasets were combined, fifteen of the twenty toxic communities ended up in fully non-toxic communities by the end of the time series for those samples. This indicates that toxicity can fracture communities. The Granger Causality test on the pro-vaccine dataset revealed that toxicity affects average nodes in a community and vice versa. This may be due to greater opinion diversity in positive conversations, while negative conversations have low opinion diversity. Our results show that in the pro-vaccine dataset, increasing toxicity significantly fractures communities, whereas in the anti-vaccine dataset, toxicity has less impact on community dynamics. Other factors, such as user suspensions or disinterest in evolving topics (e.g., political discussions), can also cause communities to fracture.

This research reveals how toxicity shapes online communities, offering insights for researchers, policymakers, and community managers. By analyzing pro-vaccine and anti-vaccine discussions, it shows how toxic behavior influences community dynamics. These findings are crucial for improving online discourse and community management, helping to predict healthier communities and mitigate toxicity.

In future work, we plan to analyze a broader range of datasets from diverse sources to enhance our findings' robustness. We also aim to conduct comparative studies across multiple online platforms to further explore toxicity's impact on community dynamics.

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