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Rethinking the US Presidential Election: Feminism and Big Data

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Abstract: *The 2020 US Presidential Election was a highly-anticipated moment for our global society. During the election period, the most intriguing issue was who would be the winner—Trump or Biden? Among the possible main themes of the 2020 election, from the COVID-19 pandemic to racism, this study focused on feminism ('women') as a main component of Biden's victory. To explore the character of Biden's supporters, this paper focused on internet spaces as a source of public opinion. To guide the data analysis, this study employed four indices from empirical studies on Big Data analytics: issue salience, attention diversity, emotional mentioning, and semantic cohesion. The main finding of this study was that the representative keyword 'women' appeared more prevalently within content related to Biden than Trump, and the keyword pairs indicated that female voters were the main reason for Trump's failure but the root cause of Biden's victory. The results of this study indicated the role of the internet as a forum for public opinion and a fountain of political knowledge, which requires more rigorous investigation by researchers.*

Keywords: US Presidential Election; Issue Salience; Attention Diversity; Emotional Mentioning; Semantic Cohesion

1. Introduction

Both of the US's two recent presidential elections featured Donald Trump as a candidate—a symbol of populism, radical right-wing politics, and nationalism. On the other side of each election, two women were spotlighted—Hillary Clinton and Kamala Harris. In the 2016 US Presidential election, Hillary Clinton was the winner of the popular vote but ultimately lost to the unexpected challenger from the Republican Party. In the 2020 election, Kamala Harris, Joe Biden's running mate, was the first woman of color to become Vice President of the United States.

The main themes of the 2020 US presidential election were arguably the COVID-19 pandemic, populism, race, and women. The year 2020 was undoubtedly dominated by the outbreak of the pandemic. Globally, as of 20 July 2021, there have been 190,671,330 confirmed cases including 4,098,758 deaths [1]. The United States was one of the most affected countries. Fueled by populism, Donald Trump embodied his nationalist vision throughout his term. He erected a border wall with Mexico, withdrew from the Paris Agreement, took 'fake news' into the mainstream, challenged the security bargain with NATO, and triggered a US-China trade war. The murder of George Floyd fueled a conversation about systemic racism in the US. 2020 also saw another year of women running in the presidential election. Joe Biden, a presidential candidate from the Democratic Party, picked Kamala Harris as his vice presidential running mate.

The most impressive aspect of the 2020 US Presidential Election was yielding the first woman of color Vice President of the United States. In other words, this election can be interpreted as a victory of a century-long battle for women's suffrage in the United States. It has been claimed that Trump's defeat in the 2020 election was due to his imprudent responses to the COVID-19 outbreak [2]. For instance, he consistently downplayed the risk of COVID-19, which led to substantial criticism [3]. Moreover, his administration signaled a formal withdrawal from the World Health Organization (WHO) [4]. He and his followers refused to embrace basic health precautions such as wearing masks and using hand sanitizers [5].

Arguably, the 2020 US Presidential Election could be viewed as an arena of struggle between feminists and their opponents. “Trump’s surprise win in 2016 galvanized once-politically quiescent women” [6] (p.72). The shock and anger “prompted a resurgence of feminist energy not seen in decades” [6] (p.73). This energy led to a new surge in feminism as an organized political movement combined with flashpoints of digital protests, such as putting the hashtag #MeToo on their social media accounts [6]. This movement was part of what led to women’s victories in the 2018 midterms which saw the “retaking the US House of Representatives for the Democrats, and six women declar[ing] their candidacy for president in 2020” [6] (p.72). In this light, the #MeToo movement and predominant feminists’ political activity became a salient issue among the US public.

To measure the main determinant of the results of the US presidential election, we here consider the internet space as a public forum that reflects the US public’s perceptions of the candidates. When it comes to exploring issue salience on the internet, topic modeling is a useful statistical tool and network analysis provides a helpful analytic approach [7]. Some researchers have attempted to measure and analyze public opinion via the internet. In this vein, internet data has become useful for researchers aiming to predict the possible outcomes of elections. Michael and Agur regard Twitter as a communication platform between the public and political stakeholders [8]. Kwak and Cho attempted to analyze social media data to measure public opinion during the election period [9]. Skoric, Liu, and Jaidka reviewed the data from 74 published sources in the literature, exploring estimates of electoral outcomes and public opinion to examine whether social media has predictive power [10]. They concluded that social media data will not replace surveys as a means of examining public opinion, but it does provide useful metrics and insights for public opinion research [10]. In all of the empirical studies, researchers looked at social media as a primary source for mining information on public opinion. This study argues that looking into internet space *per se*. is a novel and useful strategy, which considers the internet similar to a survey of public opinion.

This paper aims to explore whether feminism was a substantial and influential factor in determining the results of the US 2020 Presidential Election by focusing on the internet as a source of public opinion. This paper will test whether feminism is a useful keyword for deciphering the complexity of public opinion surrounding the election. In the next part, the study’s conceptual and theoretical background is introduced. After that, we consider the research methods and material for analysis. Subsequently, the results are presented in the format of bar charts, followed by a discussion section. Finally, it culminates with some concluding remarks and possible lessons for the future.

2. Materials and Methods

2.1 Material and Data Collection

The data set of this study was established by utilizing *Webometric Analyst 2.0* (API methods) to gather data from *Bing.com*. Data collection was performed on 2 November 2020. The keywords for this study consist of three parts: 1. Candidates’ names (Donald Trump and Joe Biden), 2. ‘issue word’ or ‘context word’ (women), and 3. the name of US States (e.g., Alabama, California, etc.).

Online discourse data pertaining to both candidates were collected one day before Election Day on November 3, 2020. Using the Boolean equation, the search terms were constructed as follows: candidate names, issue words, the names of the 51 states. The keyword for the topic-specific search scope was ‘women’. For example, one of the search strings was “Biden Women Alabama”. Thus, a total of 102 searches (2 * 51) were entered. During the data collection period, *Bing.com API* was employed through *Webometric Analyst 2.0* [11]. 51,560 web pages were collected for this paper. Among the collected web pages, 22,975 were related to Trump, and 28,585 were related to Biden. The relevance of each candidate was determined by their name search query.

2.2 Methods

This paper looked into cognate empirical research and attempted to apply a multimodal big data analysis consisting four relevant indices to analyze issue salience within online spaces. There were four indices for investigating publicization of issues throughout the internet space, and they are 1) *issue salience* [7], 2) *attentional diversity* [12], 3) *emotional mentioning* (also known as sentiment analysis) [13] and 4) *semantic cohesion* (also known as cluster analysis) [14]

Issue salience [7] entails the investigation of salient keywords through a software program. Chykina and Crabtree suggest that issue salience can be measured through Google searches (trends) [15]. Chykina and Crabtree investigated the case of illegal migrants’ sensitive agendas such as their deportation concerns by looking at the frequency of the search phrase "will i be deported" [15] (p. 2). This index is useful to consider whether "Trump" and "Biden" were salient keywords in light of feminism. To measure this index, search engines (such as *Bing* and *Google*) refine and provide the information users are searching for based on their own algorithms. Therefore, the gap between the two candidates can be examined through the frequency of returned URLs.

Attentional diversity is concerned with online readerships' degrees of attention [12]. This index can be traced either by examining themes (frames) or information spots (websites). Park *et al.* focused on how readers paid attention to specific news frames in order to measure their popularity, which might, in turn, have an impact on readers' political and social understanding [12]. An *attention diversity* index helps us to illustrate which issue is useful to consider within the research. Park and Park investigate degrees of attention among top websites that significantly attracted their readerships [16]. This indicator is useful in measuring the volume of the public interest by investigating their preferred source of information. It can be measured by classifying the types of organizations that produced online information on each issue. The distribution of the hosting domains of the URLs enables us to examine the characteristics of the two candidates.

Emotional mentioning is also known as sentiment analysis. Yoon and Chung examined words/phrases according to the sentiments they harbored (either positive or negative) [13]. Norambuena *et al.* applied this method to measure opinions and emotions from reviews of scientific studies [17]. This index enables us to measure and evaluate the emotions and latent opinions of internet users—that is, measure the public's emotional response. It identifies users' emotional support by examining the degree of emotions (either positive or negative) associated with the candidate on the page.

Semantic cohesion is also known as cluster analysis or semantic network analysis [14]. Chung *et al.* conducted a cluster analysis to enhance the thoroughness of their effective thematic analysis [18]. They presented their data based on quantitative analysis (co-word matrixes and network diagrams) and qualitative analysis (thematic analysis with examples). This index is useful to detect which themes were predominant among the general public. It helps us to determine whether there are shared characteristics between each candidate and in what context or subject. This study applies *Webometric Analyst 2.0* to explore and present results according to the above-mentioned indices, which measure the publicization of political issues within internet spaces.

This paper mainly yields its results from quantitative analysis of the data, but it attempts to conduct qualitative interpretations of the given results. Chung *et al.* used a thematic approach to interpret and validate data from a co-word network analysis (semantic network analysis) [18]. Park and Lim conducted a qualitative tagging analysis to measure the quality of North Korean propaganda on YouTube [19]. Through their studies, they tried to explore communication patterns in addition to their qualitative tagging analysis. Among these analytic approaches, the former approach of thematic data analysis is applicable to the results of this study (for *semantic cohesion*). Hence, this study will present the results of *semantic cohesion* as interpreted through thematic analysis.

3. Results

In terms of the share of issues in online spaces, Trump clearly lacked purchase against Biden with regards to feminist concerns. In 41 states out of 51, Biden was prominently mentioned with regard to women-related information. In California, where the Democratic party is strong, Biden had a 68.52 percent difference compared to Trump (787-467=320. 320/467=0.6852).

3.1 Issue Salience

Issue salience is calculated by taking logarithms of the values, i.e., the number of returned URLs. To explore *issue salience*, this study explored the relationship between the selected representative keyword, 'women', and the presidential candidates' names, Trump and Biden. The results are shown in Figure 1.

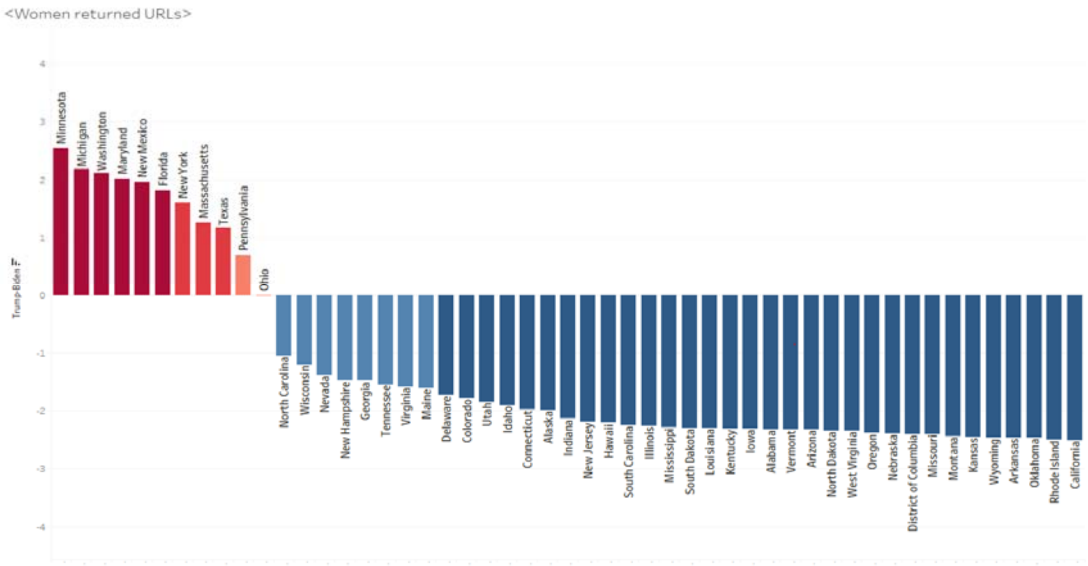

Figure 1. Returned URLs relating to the keyword ‘women’

In Figure 1, the red bars represent the *issue salience* of Trump, and the blue ones indicate the *issue salience* of Biden. For instance, taking Ohio state as an example, the red bar on that state means Trump gained more *issue salience* than Biden in Ohio. Considering the overall data provided in Figure 1, Biden gained more *issue salience* than Trump in general (Biden was more salient in 40 states vs. Trump in 11 states). Some might argue that this data suggests feminists and feminist-friendly voters supported Biden. However, it would be premature to assume that feminists supported Biden and Harris during their presidential election due to this index alone. To verify this claim, it is essential to also look at the results from the *emotional mentioning* and *semantic cohesion* indices.

3.2 Attention Diversity

This study examines *attention diversity* by measuring frequency and standardized values. Standardized values refer to values divided by the maximized frequency value. Standardized values are usually multiplied by 100 in order to enhance their recognizable presentation. In this study, the coders deleted the frequency values and re-edited them. The results are summarized in Table 1.

Table 1. Attention Diversity of Websites Related to Biden and Trump

Rank	Biden	Frequency	Standardized Values	Trump	Frequency	Standardized Values
1	realclearpolitics.com	121	100.00	trumpstoreamerica.com	60	100.00
2	insidehighered.com	81	66.90	realclearpolitics.com	56	93.30
3	youtube.com	51	42.10	slate.com	53	88.30
4	washingtonpost.com	51	42.10	youtube.com	51	85.00
5	thehill.com	51	42.10	wsj.com	51	85.00
6	theguardian.com	51	42.10	washingtonpost.com	51	85.00
7	politico.com	51	42.10	usatoday.com	51	85.00
8	nytimes.com	51	42.10	time.com	51	85.00
9	newsmax.com	51	42.10	thehill.com	51	85.00
10	independent.co.uk	51	42.10	theguardian.com	51	85.00
11	foxnews.com	51	42.10	theatlantic.com	51	85.00
12	cbsnews.com	51	42.10	politico.com	51	85.00
13	breitbart.com	51	42.10	nytimes.com	51	85.00

14	apnews.com	51	42.10	newsweek.com	51	85.00
15	news.yahoo.com	51	42.10	newsmax.com	51	85.00
16	msn.com	51	42.10	nbcnews.com	51	85.00
17	forbes.com	51	42.10	independent.co.uk	51	85.00
18	dailymail.co.uk	51	42.10	huffpost.com	51	85.00
19	abcnews.go.com	51	42.10	foxnews.com	51	85.00
20	washingtonexaminer.com	51	42.10	facebook.com	51	85.00

With the exception of Trump Store America (www.trumpstoreamerica.com), media websites were the main destinations that caught the public's attention. Based on the top 20 websites for both camps, the public was inclined to visit YouTube (www.youtube.com) (3rd for Biden and 4th for Trump), Real Clear Politics (www.realclearpolitics.com) (1st for Biden and 2nd for Trump), Washington Post (www.washingtonpost.com) (4th for Biden and 6th for Trump), Politico (www.politico.com) (7th for Biden and 12th for Trump), The Independent (www.independent.co.uk) (10th for Biden and 17th for Trump), and Fox News (www.foxnews.com) (12th for Biden and 19th for Trump). The public was inclined to rely on news media as their primary source of information regarding Trump and Biden. Moreover, the media plays a significant role in establishing public perceptions of these candidates.

3.3 Emotional Mentioning

To investigate *emotional mentioning*, this study first used *Webometrics* for data collection, then used Bing.com to scrape the texts available from the webpages. Finally, the coders imported the collected texts into NodeXL to extract words with positive and negative sentiments based on NodeXL's sentiment analysis dictionary, which is a built-in analytic function within NodeXL. The analysis indicates that the frequency of positive words (Biden: 31,898 words, 55.69%; Trump: 24,548 words, 56.49%) was slightly higher than the negative words (Biden: 24,979 words, 44.31%; Trump: 18,911 words, 43.51%). Based on NodeXL's sentiment dictionary, this study was able to detect words with positive and negative sentiments. For immeasurable words, NodeXL put them into a non-categorized words basket. This study considered non-categorized words as dummy values, so these words were excluded from the analysis. Two lists of the most popular 20 words with positive and negative sentiments are summarized in Table 2 and Table 3.

Table 2. Top 20 words conveying positive emotions

Rank	Biden	Count	Standardized Values	Trump	Count	Standardized Values
1	Win	3126	100.00	Win	1913	100.00
2	Lead	3027	96.83	Support	1646	86.04
3	Support	2372	75.88	Victory	665	34.76
4	Endorse	848	27.13	Right	372	19.45
5	Top	637	20.38	Endorse	355	18.56
6	Work	615	19.67	Approve	346	18.09
7	Supporter	520	16.64	Promise	284	14.85
8	Victory	512	16.38	Success	260	13.59
9	Supreme	436	13.95	Favor	254	13.28
10	Better	365	11.68	Appeal	197	10.30
11	Advantage	360	11.52	Safe	193	10.10
12	Strong	354	11.32	Protect	192	10.04
13	Free	324	10.37	Clear	171	8.94
14	Favor	315	10.08	Fast	161	8.42
15	Best	309	10.89	Educate	155	8.10
16	Good	307	9.82	Progress	155	8.10
17	Clear	305	9.76	Welcome	154	8.10
18	Super	274	8.77	Good	145	7.60

19	Great	261	8.35	Enough	143	7.76
20	Promise	240	7.68	Advantage	138	7.21

In Table 2, nine words were commonly associated with both candidates. They were ‘win’ (1st for both), ‘support’ (2nd for Trump and 3rd for Biden), ‘victory’ (3rd for Trump and 8th for Biden), ‘endorse’ (5th for Trump and 4th for Biden), ‘promise’ (7th for Trump and 20th for Biden), ‘favor’ (8th for Trump and 14th for Biden), ‘clear’ (13th for Trump and 17th for Biden), ‘good’ (18th for Trump and 16th for Biden) and ‘advantage’ (20th for Trump and 11th for Biden). Their common emphasis implied the importance of the candidate’s values and hopes for victory.

Table 3. Top 20 words conveying negative emotions

Rank	Biden	Count	Standardized Values	Trump	Count	Standardized Values
1	Assault	456	104.28	Protest	397	100.00
2	Issue	434	99.25	Criticism	360	90.68
3	Inappropriate	371	84.84	Attack	325	81.86
4	Allegation	315	72.03	Lose	227	57.18
5	Concern	292	66.77	Crime	222	55.92
6	Rival	278	63.57	Racist	210	52.90
7	Break	278	63.57	Accusation	199	50.13
8	lost	268	61.29	Fall	193	48.62
9	Hard	254	58.08	Opponent	193	48.62
10	Die	247	56.48	Die	188	47.36
11	Racism	242	55.34	Assault	183	46.10
12	Problem	235	53.74	Break	178	44.84
13	Lose	233	53.28	Death	172	43.33
14	Crime	232	53.05	Concern	163	41.06
15	Criticism	226	51.68	Discrimination	163	41.06
16	Kill	183	41.85	Hate	156	39.30
17	Conservative	175	40.02	Issue	145	36.52
18	Uncomfortable	166	37.96	Hard	135	34.01
19	Death	164	37.50	Virus	119	29.98
20	fall	162	37.05	limit	114	28.72

In Table 3, eleven words were commonly associated with both candidates. They were ‘criticism’ (2nd for Trump and 15th for Biden), ‘lose’ (4th for Trump and 13th for Biden), ‘crime’ (5th for Trump and 14th for Biden), ‘fall’ (8th for Trump and 10th for Biden), ‘die’ (10th for both), ‘assault’ (11th for Trump and 1st for Biden), ‘break’ (12th for Trump and 7th for Biden), ‘death’ (13th for Trump and 19th for Biden), ‘concern’ (14th for Trump and 5th for Biden), ‘issue’ (17th for Trump and 2nd for Biden), and ‘hard’ (18th for Trump and 9th for Biden). Many of the words related to criminal issues may have been related to the candidates’ past faults (such as sexual assault allegations). These words are associated with negative propaganda directed at the candidates’ opponents.

3.4 Semantic Cohesion

Semantic cohesion (also known as cluster analysis or semantic network analysis) measures clusters of themes among the textual data. This index enables us to investigate the main issues that public opinion on the internet was concerned with regarding Biden and Trump. In order to measure *semantic cohesion*, this study employed NodeXL to extract word pairs. The results of the 20 most salient word pairs are displayed in Table 4.

Table 4. Top 20 word pairs according to frequency

Rank	Biden	Count	Standardized Values	Trump	Count	Standardized Values
1	Vice/President	4233		President/Trump	6293	95.73
2	Former/Vice	2460	32.61	Vote/Trump	1889	28.73
3	Democratic/Presidential	1936	21.78	Trump/Administration	1003	15.26
4	South/Carolina	1271	18.95	New/York	992	15.10

5	Presidential/ Candidate	1106	14.91	Supreme/Cou rt	885	13.46
6	Presidential/ Nominee	1035	9.79	Suburban/Wo men	748	11.38
7	Democratic/ Nominee	961	8.52	North/Carolina	741	11.27
8	Women/Biden	942	7.97	White/House	710	10.80
9	Hunter/Biden	939	7.40	Covid/19	570	8.67
10	Black/Women	919	7.26	United/States	569	8.66
11	New/York	893	7.23	White/Women	534	8.12
12	Trump/Biden	839	7.08	Women/Voter	530	8.06
13	North/Carolina	832	6.88	New/Hampsh ire	513	7.80
14	Biden/President	829	6.46	Trump/Win	499	7.59
15	Biden/Lead	809	6.41	Men/Women	489	7.44
16	Biden/Win	789	6.39	Trump/Camp aign	452	6.88
17	United/States	691	6.23	West/Virginia	361	5.49
18	New/Hampsh ire	690	6.08	Trump/Victory	360	5.48
19	Covid/19	565	4.35	South/Carolina	357	5.43
20	Biden/Campa ign	555	4.23	South/Dakota	350	5.32

Most keyword pairs related to Trump emphasized voters' support for Trump's victory in his presidential election, such as 'donald-trump', 'president-trump', 'vote-trump', 'trump-win', and 'trump-campaign'. With regard to feminism, specific pairs like 'suburban-women', 'white-women', and 'women-voter' indicate specific groups of female voters, such as 'suburban white women voters'. This suggests that female voters held the key for Trump's reelection to a second presidential term. Since the US presidential election in 1980, female voters have had higher turnout rates than male voters [20]. In terms of party identification, female voters are more inclined to identify themselves as supporters of Democrats than Republicans [20]. This means that more female voters are latent supporters of the Democratic Party rather than the Republican Party.

For Biden, most keyword pairs highlighted Biden's identity as an individual and presidential candidate, such as,'Joe-Biden', 'Vice-President', 'Former-Vice', 'democratic-presidential', 'presidential-candidate', 'presidential-nominee', and 'Democratic-Nominee'. Like Trump, there was also a focus on his victory in the presidential election, indicated by pairs like 'Trump-Biden', 'Biden-President', 'Biden-Lead', and 'Biden-Win'. Regarding pairs related to female voters, two pairs were salient: 'women-Biden' and 'black-women'. According to Igielnik, black women are the most reliable supporters of the Democratic Party [20]. In the 2020 election, black women were powerful supporters of Biden and helped him gain his victory [20]. Based on the results suggested in Table 4, a semantic network analysis was subsequently implemented. The results for Biden can be seen in Figure 2 and those for Trump are presented in Figure 3.

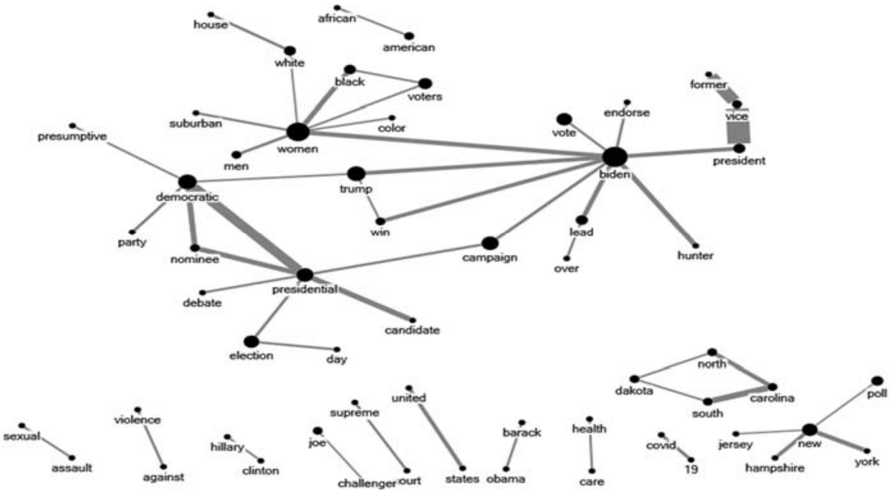

Figure 2. Semantic Network for Biden

Figure 2 illustrates the semantic network of Biden-related keywords. The main cluster is concerned with Biden's background (such as ‘joe’, ‘former’, ‘vice’, ‘president’, and ‘hunter’). Contrary to Trump’s semantic network, election-related keywords were not overwhelmingly present. In addition, women-related keywords are directly connected to ‘Biden’—the main keyword. Another difference between Biden and Trump’s semantic networks is that ‘black’ and ‘women’ were the prominent women-related keywords for Biden. Echoing the results from Table 4, black women voters were marked as a push factor for Biden’s victory.

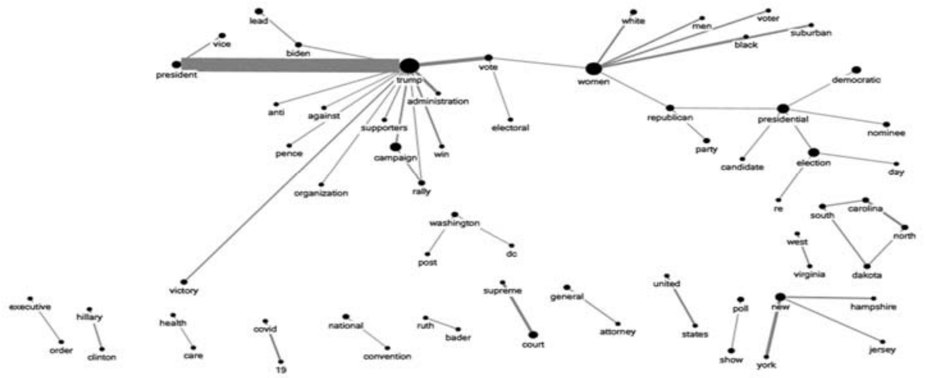

Figure 3. Semantic Network for Trump

In Figure 3, the semantic network visualizes Trump-related keywords via network mapping. Trump is the main keyword and the immediate cluster indicates hopes for Trump’s victory in the 2020 presidential elections (‘win’, ‘victory’, ‘rally’, ‘campaign’, ‘president’, and ‘vote’). Subsequent clusters illustrate keywords related to women such as ‘black’, ‘white’, ‘women’, ‘voter’, and ‘suburban’. Looking at the thickness of the links, ‘women’ is more likely to be connected to ‘men’, ‘voter’, ‘white’, and ‘suburban’. Subsequently, the coders searched for a combination of the keywords (white suburban women voter) using an internet search engine. The results returned suggested that losing support from female voters was the main determining factor of Trump’s defeat (examples: [21-23]). The second prominent cluster thus demonstrates Trump’s insurmountable stumbling block in his reelection campaign. Considering Figures 2 and 3, the results show that Biden was supported by more women voters regardless of their ethnicity.

4. Concluding Remarks

This study has examined the internet space as a source of public opinion in light of the 2020 US Presidential Election. Specifically, it looked into feminism-related public opinion by investigating relevant keywords. Considering the results from four indices (*issue salience, attention diversity, emotional mentioning,* and *semantic cohesion*), there are four major findings of this study. First, feminist keywords associated with Biden were more likely to be salient in more US states (40 States) than Trump (11 States). Second, the public relies on media outlets to gain their information about presidential candidates (relevant to both Trump and Biden). Some British outlets like The Guardian, The Independent, and The Daily Mail were sources of information that drew public attention. Third, most positive keywords implied the candidates' victory, while search terms associated with negative emotions implied the possible circulation of black propaganda about the candidates. Finally, semantic cohesion analysis found that feminism-related word pairs were associated with both Trump and Biden. These word pairs identified female voters as supporters of Biden.

The findings from examining the internet as a space of public opinion confirm the conclusion of this study. From this case, this study was able to indicate the main features of public opinion. Internet data illustrates the salient themes, representative emotions, and sentiments among the public, and their information sources. Before this research, exploring the character of public opinion presented a big challenge for social scientists. However, by approaching the internet as a source of big data, future researchers will be able to explore more insights with regards to public opinion and perception. The implications for the results can be summarized into five points. First, Trump's messages lacked freshness. His messages on the internet were saturated by Trump's victory, which could not appeal to the voters' minds. Second, Trump failed to build friendly images than Biden. Considering the top 20 words with positive emotion, the number of mentionings for Biden outnumbered Trump. Third, females raised more voices in US politics via online media. Fourth, the internet has become one of the significant impactful factors for the election as a forum for the general public. Finally, the internet might provide the minority to raise their impacts on the real world as long as they have sound and plausible messages for the public.

Certainly, this study was limited in scope in that it only looked at certain elements (quantitative aspects like degree of public attention and macro-level cognitive patterns) of the internet. Further studies undertaking different large-scale assessments are necessary. However, it did offer a guidepost for briefly looking at public opinion on the internet. The authors hope this study will serve as a humble platform for drawing out future helpful insights into public opinion.

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Conflicts of Interest: "The authors declare no conflict of interest."

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