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Building Images of "President Trump": Comparing Co-evolutions of the Trade War Discourse between Influencers and Regular Users on Twitter

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Abstract

Using semantic network analysis, this paper examines how three types of Twitter influencers and the regular Twitter users frame "President Trump" in the discourses of Trade War. In addition to revealing the central words and word clusters adopted by the different categories of Twitter users, this paper also studies how central words co-evolved over time between three types of Twitter influencers and regular users by using coherency and time lag analysis. Overall, we discovered that three types of Twitter influencers all took a negative stance on illustrating the President Trump's image, while the regular Twitter users demonstrated polarized attitudes toward it. The significant time lags between the highly co-evolved word pairs indicated complicated interactions between Twitter influencers and regular Twitter users.

1. Literature Review

1.1. Political Discussions and Polarization on Social Media

Social media are gaining substantial presence in today's political landscape [1]. They are often described as online public spheres for political discourses [2]. Despite the early euphoria about social media's potential for bringing global democratization [3] and allowing cross-cutting interactions to promote the exchange of different political views [4], researchers are increasingly concerned about social media's role in facilitating polarization [5]. Specifically, the echo-chamber effects with more polarized views have been found in the studies of political discourses on Twitter [6, 7].

With the rise of social media, there emerges a new type of celebrity – social media influencers, the individuals who influence others in online social networks [8]. Research has found that polarization could allow for influencers to maintain their social dominance and become even more influential on social media [9]. Social media influencers have different types. Understanding how different types of influencers interact with the regular users thus becomes a critical task for social media researchers.

1.2. Types of Social Media Influencers

Social media influencers are usually categorized by audience size, although the number for each tier could vary by platform. A widely adopted classification divides social media influencers into the three categories of mega, macro, and micro influencers [10, 11, 12].

Mega influencers are the highest ranked category with more than a million followers [11]. But their engagement with followers is rather low [10]. Their followers are often highly diverse with different topic interests [12]. *Macro influencers* are in the tier with 100K to up to a million followers [10]. Compared to mega influencers, they are easier to connect with. *Micro influencers* are classified to have a follower base ranging from 10,000 to no more than 100K [13]. Despite the relatively smaller number of followers, micro influencers are considered to have a stronger relationship with and be more targeted to their followers than macro and mega influencers for being more accessible and authentic [8].

Different from much existing research focusing on social media influencers' persuasive impacts on behavioral outcomes [7] [8] [9] [10], we decide to adopt a semantic approach to understand if and how influencers' chosen words in political discourse are related to the regular users' on social media. By selecting the U.S.-China Trade War as a case study, we examine how different types of social media influencers and regular users discuss President Trump respectively and how their discourses co-evolve over time.

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1.3. The U.S.-China Trade War

The trade tensions between the U.S. and China scaled up when President Trump signed an executive memorandum launching a Section 301 investigation into China's intellectual property practices and threatened extra tariffs on imports from China in March 2018 [14]. After that, the two countries went through several rounds of tariff escalations. On January 15, 2020, they officially signed a phase one trade deal [15]. This trade war between the U.S. and China is alleged to be the largest of its kind in the global market in the past 50 years [16]. By choosing the Trade War as the study context, we first identify the different types of influencers by follower size in the relevant discourses on Twitter. Focusing on the tweets mentioning President Trump, we then study the influencers' and the regular users' tweets from a semantic perspective and how their Trade War discourses co-evolved over time.

2. Methods and Research Questions

2.1. Semantic Network Analysis of Social Media Discourses

Semantic network analysis (SMA) is a form of content analysis identifying the network of associations between words expressed in a text [17]. Rooted in the cognitive paradigm [18] and the tradition of frame semantics in linguistics [19], scholars have argued that words are hierarchically clustered in memory [20]. Thus, spatial models that illustrate the relations among words are representative of meaning [21]. Through examining the visibility and co-occurrence of vocabularies in texts, salience of words can be identified, and the related framing strategies could be explained.

Most recently, SMA has been used for analyzing social media discourses on health care [22], nature disasters [23], political campaign [24], and social movements [25]. These studies mainly used centrality analysis and cluster analysis to understand the framing strategies used in social media discourses. Along with these studies, our research uses semantic network analysis to examine how different Twitter influencers and regular Twitter users built the images of "President Trump" in the discourses of Trade War.

Four semantic networks were created based on the analysis of word co-occurrence. They are the semantic networks of mega influencers' tweets (MEGA), macro influencers' tweets (MACRO), micro influencers' tweets (MICRO), and regular users' tweets (REGU). The related research questions are:

R_1: What are the most central words in MEGA, MACRO, MICRO, and REGU respectively?

R_2: What are the largest word clusters in MEGA, MACRO, MICRO, and REGU respectively?

R_3: What are the most central words in the largest word clusters of MEGA, MACRO, MICRO, and REGU respectively?

2.2. Using Coherencies to Examine the Co-evolutions of Social Media Discourses

Coherency is a measure of association between two time series. It reflects how well correlated two processes are. Specifically, using spectral analysis or frequency domain analysis, coherence squared, defined as analogous to the squared correlations coefficient [26], can be calculated to demonstrate the degree to which individual nodes' changes are related, and how they co-evolve. The slope of the phase spectrum can also be examined to ascertain the time lag to determine potential direction of causality between highly co-evolved pair of nodes. This approach has been used to examine co-evolutions of international networks and news frames [27].

This research uses coherency and time lag analysis to examine how the frames adopted by regular Twitter users co-evolved with the frames adopted by mega, macro and micro influencers. Since the coherency analysis produces a matrix of relations, a network analysis can thus be conducted.

Three coherency networks were created based on the analysis of how the frequency of the most central words in REGU co-evolved with the frequency of the most central words in MEGA, MACRO, and MICRO. They are the coherency networks of mega influencers' and regular Twitter users' tweets (MEGA-REGU), macro influencers' and regular Twitter users' tweets (MACRO-REGU), and micro influencers' and regular Twitter users' tweets (MICRO-REGU). This research raises the following questions to identify the co-evolutions of the tweets on President Trump in the discourses of Trade War:

R_4: How many clusters are there in MEGA-REGU, MACRO-REGU, and MICRO-REGU respectively?

R_5: Which set of words are highly co-evolved in each cluster of MEGA-REGU, MACRO-REGU, and MICRO-REGU?

R_6: What are the time lags between the highly co-evolved word pairs?

3. Data and Procedures

3.1. Data

Using Crimson Hexagon [28], we first searched the four key phrases “China U.S. trade war”, “U.S. China trade war”, “trade war”, and “trade conflict” among the Twitter users whose profile locations are the U.S., to identify all the possible tweets associated with the most recent U.S.-China Trade War from March 22, 2018 to March 22, 2020. Specifically, Crimson Hexagon uses the Boolean searching. An “or” operator was used between the four phrases to search for Tweets containing either of the four phrases. All the tweets extracted from the four search queries were downloaded, and duplicates have been removed through using the “distinct” function in *R*. We then identified 16,418 original English tweets created by 9,387 Twitter users, containing the word “Trump”, which constituted the sample for subsequent analyses.

Table 1 lists the number of original tweets produced by the four types of Twitter users. While regular users created the greatest number of original tweets, mega influencers had the greatest number of original tweets per author. Table 2 lists the number of original tweets created by the 30 mega influencers. Among the 30 mega influencers, 24 are media organizations, with 2 media programs, 3 democrats, and 1 unaffiliated independent. According to mediabiasfactcheck.com, 6 out of 24 media organizations are moderately to strongly biased toward liberal, with 13 having a slight to moderate liberal bias, 2 having minimal bias, and 3 being slightly to moderately conservative in bias.

Table 1. Number of tweets by types of Twitter authors

Author Type	Authors	Posts	Post/Per Author
Mega (follower>1million)	30 (0.33%)	160 (0.97%)	4.39
Macro (follower: 100000~1million)	196 (2.09%)	416 (2.53%)	2.12
Micro (follower: 10000~100000)	1,090 (11.6%)	2,404 (14.62%)	2.21
Regular (follower<10000)	8,070 (85.97%)	13,462 (81.87%)	1.67

Table 2. Number of tweets by 30 MEGAs

@business **LC*	33	@nprpolitics **LC*	2
@Newsweek **L*	25	@nytimes **LC*	2
@businessinsider **LC*	19	@nytimesworld **LC*	2
@washingtonpost **LC*	13	@politico **C*	2
@CNBC **LC*	11	@FastCompany **LC*	1
@thehill **C*	10	@GeorgeTakei†	1
@FortuneMagazine **RC*	7	@Nightline†††	1
@CNNPolitics **L*	6	@NYMag **L*	1
@ABCWorldNews **LC*	3	@PBS **LC*	1
@RollingStone **F*	3	@SenFeinstein†	1
@YahooNews **LC*	3	@tedlieu†	1
@chicagotribune **RC*	2	@THR **LC*	1
@LouDobbs ††	2	@TODAYshow†††	1
@MSNBC **L*	2	@USATODAY **LC*	1
@NBCNews **L*	2	@WSJ **RC*	1

Notes. **L*: moderately to strongly biased toward liberal; *LC*: slight to moderate liberal bias; *C*: least biased; *RC*: slightly to moderately conservative. † Democrats, †† Unaffiliated independent; ††† Media programs

Among the 196 macro influencers, 93 are media organizations. The media organizations with liberal bias (e.g., @YahooFinance, @thinkgprogress) created the greatest number of tweets. The majority of the 86 individual macro influencers are media professionals (e.g., @mitchellvii, @andrewrsorkin, @nycjim). 16 macro influencers are other organizations and online communities (e.g., @CSIS, Center for Strategic and International Studies).

As shown by the bios, the identities of the 1,090 micro influencers and 8,070 regular Twitter users are much more diverse than those of mega and macro influencers. The most frequent identities are husband and dad, wife and mom, and animal lovers. While the frequent hashtags (e.g., #resist, #theresistance, #fbr, and #resistance) used by micro influencers mainly demonstrated negative attitudes toward President Trump, the most frequently used hashtags (e.g. #resist, #maga) by the regular Twitter users reflected polarized attitudes toward President Trump.

3.2. Procedures

Using the tidytext package for *R*, this paper first did the text mining of the 16,481 English tweets. The text corpus was categorized into MEGA, MACRO, MICRO, and REGU based on different author types. After removing the stop words that are typically extremely common words in English (e.g., “the”, “of”, “to”, etc.), stemming was conducted through handling plural endings. The URLs and emojis were also removed. The hashtags were retained as words without the symbol “#”.

Then, four semantic networks were generated based on the measurement of word co-occurrence. Miller argued that people’s working memory had a capacity of “seven plus-or-minus two” chunks, indicating people can process seven meaningful units, plus or minus two, at a time [29]. Based on this argument, this study used the five-chunk to define the word link. In order to clearly identify how different types of Twitter users discuss President Trump, this research only used the 5-word sliding windows that contained the word “Trump” for building semantic networks. Besides the extreme frequent words “Trump”, “China”, “trade”, and “war”, words that occurred within five words of each other were considered connected regardless of the number of words separating the terms.

The four semantic networks were examined through Gephi [30], a software for network analysis, graphics, and statistical computing. We first used Gephi to calculate the normalized eigenvector centralities of each word in the four semantic networks. Eigenvector centrality indicates a word’s overall influence in a semantic network [31]. A word’s eigenvector centrality increases relatively if it co-occurs with more central words.

We then used Gephi to calculate the clusters of networks by conducting modularity analysis [32] that measures how well a network is compartmentalized into groups or communities. Modularity ranges from 0 to 1. Networks with high modularity have dense connections between the words within the groups but sparse connections between words in different groups.

Also, the OpenOrd layout in Gephi [33] was used to create visual maps of semantic networks. In the visualizations, the size of each word’s label depends on its eigenvector centralities, such that the larger the object, the more central a word is in the description of Trump in the Trade War. Lines on the maps indicate the presence of a relationship between each pair of words. The thicker lines represent a stronger relationship between two words. Also, the shorter distance between two words, the closer relationship there is between them.

To study the co-evolution of words used in tweets, this paper first calculated the daily frequencies (732 time points) of the ten words with the greatest normalized eigenvector centralities in the top ten largest word clusters of REGU, MEGA, MACRO, and MICRO. Then, the frequencies of the most central words in REGU at time *t* were correlated with the frequencies of the most central words in MEGA, MACRO, and MICRO at *t* +1 for the entire time series, creating a series of vectors of correlations, ***r***. These vectors were Fourier spectral analyzed producing three coherence matrixes (MEGA-REGU, MACRO-REGU, MICRO-REGU). A modularity analysis was conducted using Gephi to explore which set of words were highly co-evolved, and a time lag analysis was conducted to determine the potential direction of causality between the highly co-evolved pair of words.

4. Results

Table 3 illustrates the overview of the four semantic networks, including the number of words and links in each network, the network density, modularity, and the number of clusters in each network. The results are discussed below.

From MEGA to REGU, while the network densities and modularity were in decreasing order, the number of word clusters was the opposite. MEGA is the densest with the greatest modularity and the least number of word clusters. REGU is the sparsest with the smallest modularity and the greatest number of word clusters. This is in coincidence with the fact that MEGA mainly reflects the opinions of media organizations that are biased toward liberal, but REGU illustrates thoughts of regular Twitter users that have much more diverse backgrounds.

Table 3. Overview of the four semantic networks

	MEGA	MACRO	MICRO	REGU
Words	229	513	1,163	69,283
Links	815	1,829	6,599	22,228
Density	0.031	0.014	0.01	< 0.000
Modularity	0.921	0.91	0.799	0.702
Clusters	69	106	191	310

To answer $\mathbf{R_1}$, Table 4 lists the ten words with the greatest normalized eigenvector centralities in MEGA, MACRO, MICRO, and REGU.

Table 4. Most central words in MEGA, MACRO, MICRO, and REGU

	MEGA	Eigen	MACRO	Eigen
1	administration	0.1830	administration	0.1382
2	economy	0.1578	billion	0.1233
3	threat	0.1477	america	0.1171
4	set	0.1359	farmer	0.1067
5	tweet	0.1345	xi	0.1027
6	fear	0.1307	hurt	0.0994

7	mean	0.1271	win	0.0988
8	hit	0.1240	bailout	0.0968
9	xi	0.1229	strategy	0.0957
10	cost	0.1162	global	0.0937
	MICRO	**Eigen**	**REGU**	**Eigen**
1	administration	0.1061	economy	0.1161
2	economy	0.0996	farmer	0.1013
3	farmer	0.0899	administration	0.0968
4	america	0.0848	america	0.0944
5	xi	0.0793	policy	0.0804
6	tax	0.0756	maga	0.0799
7	deal	0.0740	trumptariff	0.0755
8	farm	0.0730	xi	0.0714
9	win	0.0711	new	0.0712
10	billion	0.0709	gop	0.0689

To answer **R₂** and **R₃**, Table 5 illustrates the three words with the greatest normalized eigenvector centralities in the top ten largest word clusters in MEGA, MACRO, MICRO, and REGU, as well as the percentage that the number of words in the top-10 word clusters out of the total number of words in each semantic network. More salient words in each cluster can be found in the graphic representations of MEGA, MACRO, MICRO, and REGU (Figure 1a, 1b, 1c, 1d). The network visualizations also supplement the discussions of the results. Different colors highlight the top ten largest word clusters in each network.

Table 5. Three most central words in the top ten largest word clusters in MEGA, MACRO, MICRO, and REGU

	MEGA	MACRO	MICRO	REGU
1	threat	*admin	farm	maga
	booby	strategy	billion	gop
	malaise	escalate	cost	win
***p**	**8.48%**	**8.66%**	**9.35%**	**9.93%**
2	*admin	5beijing	5beijing	trumptariff
	aid	hurting	win	resist
	*contro	cost	mean	*trumprece
p	**7.59%**	**6.50%**	**5.83%**	**9.18%**
3	economy	farmer	farmer	*admin
	global	hurt	hit	tax
	shift	hit	hurt	cut
p	**7.14%**	**6.30%**	**5.25%**	**5.75%**
4	fear	xi	economy	xi
	mean	summit	trumptariff	president
	xi	mean	job	summit
p	**6.25%**	**5.91%**	**5.01%**	**5.75%**
5	billion	global	xi	farmer
	western	spur	president	soybean
	challenge	5beijing	talk	hurting
p	**4.46%**	**5.51%**	**4.70%**	**5.37%**
6	leave	billion	threat	economy
	farmer	bailout	escalate	usa
	strategy	threat	global	2020election
p	**3.12%**	**5.31%**	**4.58%**	**4.86%**
7	tweet	policy	*admin	5beijing
	tech	strong	apple	farm
	giant	deserve	fight	cost
p	**3.12%**	**3.94%**	**4.28%**	**4.70%**
8	amid	amid	market	threat
	rising	toilet	tweet	world
	concern	brushe	backfire	idiotic
p	**3.12%**	**3.74%**	**3.98%**	**4.11%**
9	*HK	trigger	tax	hit
	ty	tax	eu	job
	protest	impend	*impeach	5beijing
p	**2.68%**	**3.35%**	**3.80%**	**3.81%**
10	summit	win	policy	business
	urge	president	reckless	market
	boycott	narcissistic	caused	stock
p	**2.68%**	**2.76%**	**3.80%**	**3.52%**

Notes. *p: the percentage of the number of words in the top-10 word clusters out of the total number of words in each semantic network. *admin: administration. *contro: controversy. *trumprece: trumprecession. *HK: Hong Kong; *impeach: impeachtrump.

To sum up, MEGA, MACRO, and MICRO all took a negative stance on framing President Trump. By emphasizing the words like *threat* and *fear*, MEGA criticized that Trump administration's controversial Trade War policies brought about domestic and global economic recession.

For MACRO, the largest word cluster connected Trump administration with negatives words like asinine, moron president, and foolish. *Hurt*, one of the most salient word in MACRO, was used a lot in describing the negative effects of Trump's Trade War policies on farmers. Another salient word *win* was often used in association with the question mark (e.g., "who is winning the trade war?")

MICRO also emphasized the negative effects of Trump's Trade War policies on farming industry and farmers. Many tweets argued that Trump's bailout for U.S. farmers was hit by the Trade War with China. Micro influencers also criticized the Trade War by using some famous anti-Trump hashtags, such as #trumprecession and #trumpcrash.

It is interesting that REGU demonstrated polarized attitudes in framing President Trump. Among the top two largest word clusters, while one was centered around some famous pro-Trump hashtags that all had close connections with the word *win* (e.g., #maga, #trumptrain, #trump2020), the other was centered around the anti-Trump hashtags (e.g., #theresistance, #resist, #trumprecession, and #trumpcrimefamily).

To answer $\mathbf{R_5}$ and $\mathbf{R_6}$, Table 6a to 6c illustrate the percentage that the number of words in each cluster out of the total number of words in MEGA-REGU, MACRO-REGU, and MICRO-REGU, the most highly co-evolved word pair in the three coherence networks, as well as the coherency and significant time lags between the highly co-evolved word pairs.

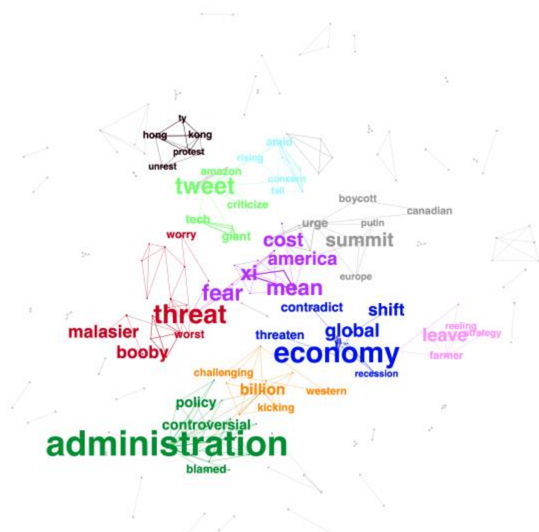

Figure 1a. Graphic representations of MEGA

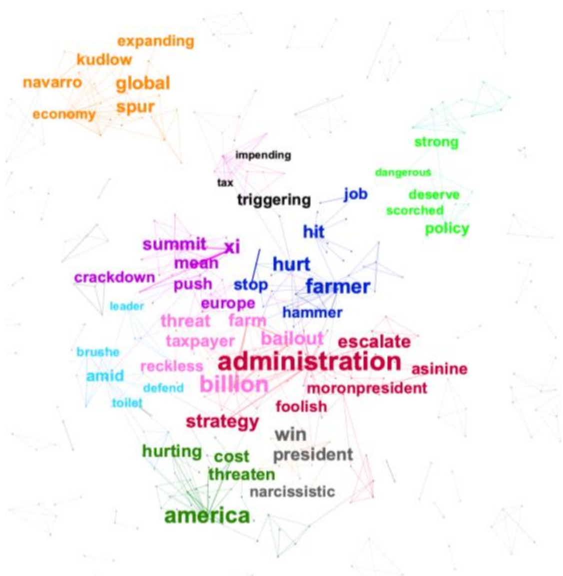

Figure 1b. Graphic representation of MACRO

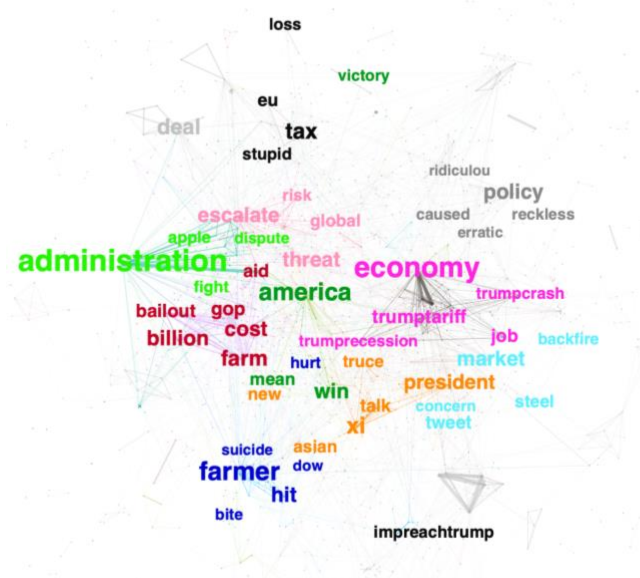

Figure 1c. Graphic representations of MICRO

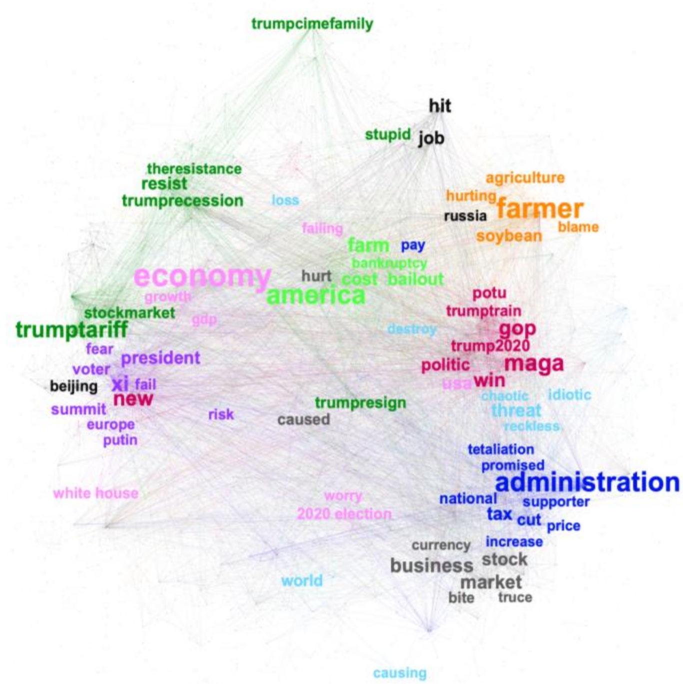

Figure 1d. Graphic representations of REGU

The most closely co-evolved word pairs in all three coherency networks were related to the truce topic. The word *truce* highly co-evolved between MICRO and REGU with no time lags. But the word *dance* in MEGA highly co-evolved with the word *truce* in REGU with a 2-day lag. After REGU demonstrated interests in the Trade War truce, Bloomberg wrote a tweet “*What the Trump-Xi trade dance means for China and U.S. stocks*” about two days later. The URL link embedded at the end of this tweet also provided the answer to this question through a news article from Bloomberg titled "*Trump-Xi Truce Does Little to Bridge Vast U.S.-China Divide*." It's quite interesting to find that the word *dance* in MACRO also highly co-evolved with the word *truce* in REGU with a 3-day lag, indicating the discourse interactions on the truce topic between regular Twitter users and news media and journalists.

Besides the tight co-evolutions of the words related to the truce topic, the coherencies of four-word pairs in MEGA-REGU (Table 6a), eight-word pairs in MACRO-REGU (Table 6b), and four-word pairs in MICRO-REGU were greater than .9.

Specifically, as shown in Table 6a, the words *agriculture* and *Canada* co-evolved with no time lags between MEGA and REGU, indicating both news media and regular Twitter users paid close attention to the Trade War's influences on agriculture industry and U.S.-Canada relations. The words *fall* in MEGA and *blame* in REGU were found highly co-evolve with no time lags. For example, while MEGA reported Wall Street shared falling, REGU emphasized who to take the blame for this. It's interesting to find that the word *investment* in REGU closely co-evolved with the word *booby* in MEGA with a 1-day lag. After Bloomberg tweeted that "Trump Trade War sets booby trap for strong U.S. economy", many REGUs discussed Trade War's effects on limiting Chinese investments.

Table 6a. Most highly co-evolved word pairs of word clusters in MEGA-REGU

P*	TWP*		C*	L*
17%	Me_aid	Re_pay	0.87	0
15%	Me_europe	Re_win	0.82	3
12%	Me_contradicting	Re_president	0.80	1
11%	**Me_agriculture**	**Re_agriculture**	**0.95**	**0**
9%	**Me_dance**	**Re_truce**	**0.99**	**2**
9%	Me_concern	Re_trumpresign	0.75	-5
7%	**Me_fall**	**Re_blame**	**0.91**	**0**
7%	Me_mexico	Re_fail	0.87	3
4%	Me_relief	Re_republican	0.84	6
4%	**Me_canada**	**Re_canada**	**0.98**	**0**
2%	**Me_booby**	**Re_investment**	**0.92**	**-1**
2%	Me_america	Re_cost	0.51	-1

Notes. *P: percentage of the number of words in each cluster out of the total number of words in the coherency network. TWP: the most highly co-evolved word pair in each cluster of the coherency network. C: coherency between the word pair. L: significant time lags between the highly co-evolved word pairs (with day as the unit). The negative lags indicate that the words in the first column of TWP appeared earlier than the words in the corresponding cells of the second column of TWP.

Illustrated by Table 6b, the words *cost*, *Europe*, and *agriculture* highly co-evolved with no time lags between MACRO and REGU, indicating that they had same interests on discussing the cost of Trade War and its effects on agriculture industry and U.S.-Europe relations. Also, the word *boil* in MACRO highly co-evolved with the word *Canada* in REGU with no time lag, implying that while MACRO paid attentions on the boiling tensions between U.S. and other countries in Trade War, REGU focused more on Trade War's effects on US-Canada relations.

The words *Mexican* and *hammering* in MACRO highly co-evolved with the words *fail* and *bailout* in REGU with a 1-day lag and a 2-day lag respectively. Specifically, one day after REGU's discussions on the failing of Trade War, MACRO discussed the positive effects of Trade War on Mexican. Two days after REGU's discussions on Trade War bailout, MACRO started to discuss that a variety of industries were hammered by the Trade War.

Furthermore, the words *investment* and *fed* (federal) in REGU highly co-evolved with the words *spook* and *narcissistic* in MACRO with a 5-day lag and a 2-days lag respectively. For example, after MACRO discussed that the Trade War spooked investors, REGU tweeted that the Trade War fears curbed investment between U.S. and China five days later. After MACRO described President Trump as narcissistic, REGU started to discuss how federal events working with the Trade War to affect the mortgage rates two days later.

Table 6b. Most Highly co-evolved word pairs of word clusters in MACRO-REGU

P	TWP		C	L
14%	Ma_texas	Re_home	0.81	1
12%	**Ma_hammering**	**Re_bailout**	**0.90**	**2**
11%	**Ma_mexican**	**Re_fail**	**0.93**	**1**
10%	**Ma_europe**	**Re_europe**	**0.93**	**0**
8%	**Ma_spook**	**Re_investment**	**0.91**	**-5**
7%	Ma_triggering	Re_consumer	0.81	-1
7%	**Ma_dance**	**Re_truce**	**0.98**	**3**
6%	**Ma_boil**	**Re_canada**	**0.98**	**0**
6%	**Ma_cost**	**Re_cost**	**0.96**	**0**
6%	**Ma_narcissistic**	**Re_fed**	**0.93**	**-2**
4%	**Ma_agriculture**	**Re_agriculture**	**0.95**	**0**
3%	Ma_farm	Re_republican	0.77	5
2%	Ma_foolish	Re_hit	0.58	-3

2%	Ma_threat	Re_threat	0.50	0

As shown in Table 6c, the words *cost*, *loss*, and *pay* highly co-evolved between MICRO and REGU with no time lags, reflecting their common interests in the discourses of Trade War. The word *fed* (federal) in REGU co-evolved closely with *fed* in MICRO with a 1-day lag. Fox example, MICRO tweeted that "*Fed's Powell Says A Long Trade War Could Hurt U.S. Economy*" on July 18, 2018; REGU then discussed this tweet one day later.

Table 6c. Most Highly co-evolved word pairs of word clusters in MICRO-REGU

P	TWP		C	L
16%	**Mi_pay**	**Re_pay**	**0.90**	**0**
13%	**Mi_truce**	**Re_truce**	**0.98**	**0**
12%	**Mi_cost**	**Re_cost**	**0.92**	**0**
9%	**Mi_loss**	**Re_loss**	**0.96**	**0**
9%	**Mi_fed**	**Re_fed**	**0.94**	**-1**
9%	Mi_farmer	Re_farmer	0.83	0
5%	Mi_mean	Re_canada	0.65	0
5%	Mi_spook	Re_investment	0.84	-5
4%	Mi_recession	Re_job	0.56	2
4%	Mi_backfire	Re_trumpresign	0.75	0
2%	Mi_aluminum	Re_republican	0.56	-2
2%	Mi_beijing	Re_beijing	0.63	0
2%	Mi_consumer	Re_stock	0.53	1
2%	Mi_dispute	Re_maga	0.52	2
2%	Mi_farm	Re_farm	0.84	0
2%	Mi_hit	Re_hit	0.72	0
2%	Mi_price	Re_price	0.54	0

5. Implications

5.1. Mass Media as Leading Influencers

We found that the majority of mega and macro influencers were mass media organizations and professionals. In other words, traditional media were still very influential in leading the discourses about the U.S.-China Trade War on Twitter. Although they haven't generated that many tweets on this topic when compared to the micro influencers and regular users, the large numbers of their followers could have boosted the impact of their tweets. For a complex topic like this, the general public might not have enough expertise to fully process the underlying implications of this topic. Therefore, mass media played a more prominent role on the topic.

5.2. Social Media Influencers' Liberal Bias

The results of Twitter profile analysis of mega, macro, and micro influencers and the semantic network analysis of their tweets reflected the liberal bias. Negative attitudes dominated the Twitter discourses on President Trump in all three types of Twitter influencers' tweets. In particular, the majority of mega influencers and almost half of the macro influencers were news media that commonly regarded as having liberal bias. This indicates that news media biased toward liberal were more adept at using social media platforms to express their political ideology.

It was also found that besides news media, many macro influencers are media professionals, such as journalists. Their critiques on Trump administration corresponded to the previous research on the liberal bias of journalists [34, 35], providing evidences on how mainstream news media and journalists using social media for agenda setting on political discourse.

Compared with mega and macro influencers, micro influencers have more diverse backgrounds and focused more on the negative effects of Trade War at the individual level, such as how bailouts for farmers was hit. It's interesting to find that micro influencers mainly used a variety of anti-Trump political hashtags, such as # trumprecession, to unite and magnify individual political viewpoints (Figure 1c).

5.3. Polarized Regular Social Media Users

Unlike the social media influencers who have demonstrated more consistency in framing President Trump, our study shows that the regular Twitter users embraced more polarized attitudes toward him. This illustrates the vast and growing gap between liberals and conservatives in the current American political landscape and resembles the "echo chambers" effects discovered in studies on political salient topics (e.g., [5] [6] [7]). However, despite the highly polarized general attitudes towards the president, regular Twitter users' discourse on the Trade War were very sparse and diversified, as shown by the low density, low modularity, and large number of word clusters found in the current study.

The words used in their discourse are more reflective of a wide range of concerns associated with the potential economic outcomes on the individual level for jobs, small businesses, and personal investments. Compared to the topics chosen by the social media influencers, which addressed the Trade War at a higher order, these topics are more down-to-earth and touch upon the everyday life of people in the U.S. The regular Twitter users also utilized political hashtags to back up their political standpoints. The two polarized word clusters in MICRO and REGU were centered around two famous political hashtags that are in sharp contrast: #resist and #maga. The more word clusters formed in the regular Twitter users' discourses thus suggest a less polarized view on the Trade War itself, despite of the highly polarized view on the role of President Trump in this battle between two countries.

5.4. Interaction between Social Media Influencers and Regular Social Media Users

This research also contributes to the current literature on studying how different types of Twitter influencers interact with regular social media users using the fine-grained coherency analysis of frequency of salient words adopted by different Twitter users. Although the coherency analysis in this research cannot provide a clear picture on who are the leaders and who are the followers in the process of political discussion on Twitter, the results of time lag analysis indicated complicated interactions between them.

The tightest co-evolutions between *dance* and *truce* in MEGA-REGU and MACRO-REGU all had significant positive time lags, indicating that news media and journalists paid close attentions and responded to the regular Twitter users' political discourse. Also, the negative words from the Twitter influencers (e.g., booby, concern, contradicting, foolish, narcissistic, and recession) mainly co-evolved with words used by the regular Twitter users with significant time lags, indicating that the Twitter influencers with liberal bias tended to reiterate their agenda settings to the public, while interacting with the regular Twitter users. However, the majority of the salient co-evolutions in MEGA-REGU and MACRO-REGU were not between the same words. It can be inferred that news media and regular Twitter users stuck to their own framing strategies when negotiating the political affairs.

Compared to the co-evolutions in MEGA-REGU and MACRO-REGU, the salient co-evolutions in MICRO-REGU mainly happened between the same words with no time lags (e.g., pay, cost, and lost). This indicates greater similarities between tweets from micro influencers and regular Twitter users. This could also be attributed to the common individual level interests between them. Furthermore, #maga, as a salient positive hashtag mainly used by the regular Twitter users, only closely co-evolved with words (e.g., dispute) used by the micro influencers, indicating closer co-evolutions of political discourses between them.

6. Limitations and Future Studies

In the current study, we did not take the Trade War-related hashtags into consideration when searching for the relevant tweets or study the use of hashtags in the tweets about the Trade War. Future research may have a closer look at the hashtags used during Trade War or use the Trade War-related hashtags as the search queries.

The co-evolution patterns that we have discovered in this study could indicate that different Twitter influencers had adopted different strategies to present themselves and connect with regular users. In order to confirm this assumption, future studies need to examine additional linguistic characteristics.

Future research should also examine the discourse co-evolutions between different Twitter influences (i.e., mega, macro, and micro influencers) so as to provide deeper understandings of the multi-level discourse interactions between Twitter influencers and the regular Twitter users. It will also be interesting to examine how micro influencers and regular users use hashtags to join in political discussions and serve as opinion leaders of local communities.

6. References

[1] F. Masroor, Q. N. Khan, I. Aib, and Z. Ali, "Polarization and ideological weaving in Twitter discourse of politicians", Social Media+Society, 5, 2019, pp. 1-14.
[2] M. Nelimarkka, S.-M. Laaksonen, and B. Semaan, "Social media is polarized, social media is polarized: Towards a new design agenda for mitigating polarization", Proceedings of DIS 2018, Hong Kong, pp. 957-970.
[3] J. Stromer-Galley, "New voices in the public sphere: A comparative analysis of interpersonal and online political talk," Javnost/The Public, 9, 2002, pp. 23-42.
[4] R. K. Garrett, D. Carnahan, & E. K. Lynch, "A turn toward avoidance? Selective exposure to online political information, 2004–2008", Political Behavior, 35, 2011, pp. 113-134.
[5] D. Demszky, N. Garg, R. Voigt, J. Zou, M. Gentzkow, J. Shapiro, and D. Jurafsky, "Analyzing polarization in social media: Method and application to Tweets on 21 mass shootings. Proceedings of NAACL-HLT 2019, pp. 2970–3005.
[6] P. Barberá, J. T. Jost, J. Nagler, J. A. Tucker, and R. Bonneau, "Tweeting from left to right", Psychological Science, 26, 2015, pp. 1531–1542.

[7] A. Gruzd, and J. Roy, “Investigating political polarization on twitter: A Canadian perspective,” Policy & Internet, 6, 2014, pp. 28–45.
[8] H. Hendriks, D. Wilmsen, W van Dalen, and W. A. Gebhardt, “Picture me drinking: Alcohol-related posts by Instagram influencers popular among adolescents and young adults”, Frontiers in Psychology, *22*, 2020. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.02991/full
[9] I. Garibay, A. V. Mantzaris, A. Rajabi and C. E. Taylor, “Polarization in social media assists influencers to become more influential: analysis and two inoculation strategies”, Scientific Reports, 9, 2019, e18592
[10] A. Ruiz-Gomez, “Digital fame and fortune in the age of social media: A classification of social media influencers”, International Journal of Communication Research, 19, 2019, pp. 9-29.
[11] L. Bullock, “How to evaluate and partner with social media influencers”, Social Media Examiner. https://www.socialmediaexaminer.com/partner-social-media-influencers/
[12] K. Ismail, “Social media influencers: Mega, macro, micro, or REGU”, CMSWire. https://www.cmswire.com/digital-marketing/social-media-influencers-mega-macro-micro-or-REGU/
[13] B. Foxwell, “A guide to social media influencers: Mega, macro, micro, and REGU,” 2020, https://blog.iconosquare.com/guide-to-social-media-influencers/
[14] J. Diamond, “Trump hits China with tariffs, heightening concerns of global trade war”, CNN. https://www.cnn.com/2018/03/22/politics/donald-trump-china-tariffs-trade-war/index.html
[15] Reuters, “What’s in the U.S.-China Phase 1 trade deal”, January 15, 2020. https://www.reuters.com/article/us-usa-trade-china-details-factbox/whats-in-the-us-china-phase-1-trade-deal-idUSKBN1ZE2IF
[16] L. D. Qiu, C. Zhan, and X. Wei, “An analysis of the China-US trade war through the lends of the trade literature”, Economic and Political Studies, 2019, 7(2), pp. 148-168.
[17] M.L. Doerfel, “What constitutes semantic network analysis? A comparison of research and methodologies”, Connections 21, 1998, pp. 16-26.
[18] P. D’Angelo, research program: “News framing as a multi-paradigmatic research program: A response to Entman”, Journal of Communication, 52, 2002, pp. 870–888.
[19] C.J. Fillmore, “Frame semantics”. Linguistics in the morning calm, 1982. pp. 111-137.
[20] A.M. Collins, and M.R. Quillian, “Experiments on semantic memory and language comprehension”. In L. W. Gregg (Ed.), Cognition in learning and memory, New York Wiley, 1972, pp. 117-138.
[21] Barnett, G.A., and J. Woelfel, Readings the Galileo system: Theory, methods and applications, Kendall/Hunt, Dubuque, IA, 1988.
[22] G.J. Kang, S.R. Ewing-Nelson, L. Mackey, J.T. Schlitt, A. Marathe, K.M. Abbas, and S. Swarup, “Semantic network analysis of vaccine sentiment in online social media”, Vaccine, 35, 2017, pp. 3621-3638.
[23] W. Liu, C.H. Lai, and W.W. Xu, “Article Title”, “Tweeting about emergency: A semantic network analysis of government organizations’ social media messaging during Hurricane Harvey”, Public relations review, 44, 2018, pp. 807-819.
[24] S.M. Eddington, C.D. Jones, and E.F. Roberts, “The communicative constitution of hate organizations online: A semantic network analysis of ‘Make America great again’”, *Social Media & Society*, 2018, pp. 2056305118790763.
[25] Y. Xiong, M. Cho, and B. Boatwright, “Hashtag activism and message frames among social movement organizations: Semantic network analysis and thematic analysis of Twitter during the# MeToo movement”, Public relations review, 45, 2019, pp. 10-23.
[26] J.M. Gottman, “Time-series analysis of continuous data in dyads”, Social interaction analysis: Methodological issues, 1979, pp.207-229.
[27] G.A. Barnett, K. Jiang and J.R. Hammond, “Using coherencies to examine network evolution and co-evolution”, Network Analysis and Mining, 5, 2015, p. 53
[28] P. Hitlin, “Methodology: How Crimson Hexagon Works”, Pew Research Center.
[29] G.A. Miller, “The magical number seven, plus or minus two: Some limits on our capacity for processing information”, Psychological Review 63, 1956, pp. 81–97.
[30] M. Bastian, S. Heymann, and M. Jacomy, “Gephi: an open source software for exploring and manipulating networks”, ICWSM, 2009, pp. 361-362.
[31] P. Bonacich, “Factoring and weighting approaches to status scores and clique identification”, Journal of Mathematical Sociology, 2, 1972, pp. 113-120.
[32] V.D. Blondel, J.L. Guillaume, R. Lambiotte and E. Lefebvre, “Fast unfolding of communities in large networks”, Journal of statistical mechanics: theory and experiment, 2008, pp. P10008.
[33] S. Martin, W.M. Brown, R. Klavans and K. Boyack, “OpenOrd: an open-source toolbox for large graph layout”, In *Visualization and Data Analysis 2011*, International Society for Optics and Photonics, 2011, pp. 786806.
[34] “Media Bias: Pretty Much All of Journalism Now Leans Left, Study Shows”, Investor's Business Daily. November 16, 2018. https://www.investors.com/politics/editorials/media-bias-left-study/
[35] C. Cillizza, “Just 7 percent of journalists are Republicans. That’s far fewer than even a decade ago”, The Washington Post. May 6, 2014. https://www.washingtonpost.com/news/the-fix/wp/2014/05/06/just-7-percent-of-journalists-are-republicans-thats-far-less-than-even-a-decade-ago/