報告論文

The Impact of COVID-19 on Direct Marketing E-commerce Platforms in Japan
- Based on a Quantitative Text Analysis of Twitter Data –

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I Introduction

The outbreak of a new coronavirus disease, known as COVID-19, had a deep impact globally. It affected agricultural distribution systems in Japan. Many people were afraid of COVID-19, so they avoided going outside. As a result, sales in the restaurant industry declined significantly. In contrast, sales of direct agricultural products marketing in E-commerce increased (MAFF, 2021).

Many studies conducted on the impact of COVID-19 on food and agriculture analysed significant quantitative changes (e. g. Konishi et al., 2021), and some studies focused on the qualitative impacts (e. g. Ellison et al., 2021). But it is still unclear about the impact of COVID-19 on perceptions of consumers and producers toward direct agricultural products marketed via E-commerce (henceforth, direct E-commerce). The perceptual gaps between consumers and producers are known to lead to several market problems (Grunert et al., 2004). This study is intended to clarify the qualitative impact of COVID-19 on direct E-commerce in Japan through a quantitative text analysis of Twitter data to identify the perceptual gaps. Because of the vast number of active users, Twitter data provides rich and useful information about people's behavior and feelings, including consumers and farmers, about direct E-commerce.

Possible discrepancies in the responses of consumers and producers towards direct E-commerce may hinder the development and expansion of the direct E-commerce market. The extent to which COVID-19 has influenced the qualitative shifts in direct E-commerce remains unclear. Therefore, the objective of this study is to answer the following research questions: (1) What are the differences between consumer's and producer's response to direct E-commerce during COVID-19 pandemic? and (2) What are the differences of the behavior and feeling about direct E-commerce before and after COVID-19?

II Method

1 Data Collection

This study was conducted in two steps: (1) Twitter data which is related to direct E-commerce in Japanese, collection using the Twitter API, and (2) quantitative text analysis to understand trends, contents, and keywords.

Tweets in Japanese were collected using the Twitter API provided by Twitter and the searchtweets Python library, that contain "Tabechoku (食べチョク)", "Pocket Marche or Pokemaru(ポケットマルシェ、ポケマル)", "Sanchoku Owl (産直アウル)", or "Sanchoku EC (産直 EC)" which is the most used keyword means direct E-commerce. All of these keywords except Sanchoku EC are the names of Japanese popular direct E-commerce platforms. To identify trends before and after outbreak of COVID-19 (2020), A total of 84,529 original Tweets, excluding Retweets, were collected, between 2019 and 2021; during this period, the outbreak started in China and then Japanese national government declared the state of emergency in response to COVID-19 three times.

2 Data Analysis

The data was prepared to analyze it in four steps: data cleaning, identifying producer's tweets, dividing tweets into three periods, and preprocessing of raw data. As a first step, data cleaning means removing URLs, emojis, Retweets, and hash tags. URLs and emoji are difficult to analyze. Retweets and hash tags are repeated too frequently that means they might be anomalies. As a second step, I collected Twitter username listed in producer's profile page of Pocket Marche to identify the Tweets posted by producer at Pocket Marche. Then, I divided 2019 – 2021 into three periods; "Before COVID period" from January 1st, 2019 to March 31st, 2020, "During COVID period" from April 1st to 6th, 2020 and from May 26th, 2020 to December 31st, 2021, and "State of Emergency" from April 7th to May 25th, 2020. These three periods help to reveal the trend before and after outbreak of COVID-19. Finally, Words were extracted from cleaned Tweets using ChaSen, which segmented each Tweet into morphemes. The extraction process involved creating a "new word" list for forcibly extracted words such as "PocketMarche" and an "ignore word" list for words that were considered nonexistent.

I used PC program named "KH Coder" developed by Higuchi (2004). It is a free software program utilized to conduct three types of quantitative content analysis to address the research questions. These analyses included frequency counting to identify commonly used words, hierarchical cluster analysis to group words with similar patterns of appearance in tweets, and the creation of a self-organizing map to explore associations between words. The self-organizing map is a type of automatic data analysis typically used for clustering words and understanding data structure. Additionally, a chi-square test was conducted to validate the observed differences between producer and consumer groups in different time periods, with several coding rules established for this analysis (see table 1). For example, any Tweet including either "発送(Shipping)" or "出品(Sell)" or "現場(Field)" is given the code "Producer". Coding words were used to characterize each tweet. The chi-square test was conducted with these codes to detect the statistical differences between producer and consumer, and each period.

Table 1 Coding Rules in This Study

Code Name	Coding Words Samples	Tweets	(%)
Producer	発送 Shipping, 出品 Sell, 現場 Field	10,235	(12.3)
Consumer	届く Arrive, 取り寄せ Order	6,785	(8.2)
Agricultural Product	米 Rice, トマト Tomato, 玉ねぎ Onion, リンゴ Apple	10,381	(12.5)
Livestock Product	牛肉 Beef, 豚肉 Pork, 牛乳 Milk, チーズ Cheese, バターButter,	3,262	(3.9)
Seafood	魚 Fish, 漁師 Fisher, 牡蠣 Oyster, 鯛 Snapper	9,637	(11.6)
Organic	無農薬 Non-Chemical, 有機 Organic, オーガニック Organic	1,058	(1.3)
Support	コロナ COVID, 応援 Cheer, 困る Trouble, 被害 Damage	1,034	(1.2)
Promotion	送料 Shipping Fee, クーポン Coupon, キャンペーン Promotion	5,632	(6.8)
Positive	嬉しい Happy, 美味しい Delicious, 良い Good, 楽しむ Enjoy	10,235	(12.3)
First Experience	初めて First Time, 最近 Recently *, 出来る be Able to **, 知る Know	6,785	(8.2)

Source: Collected Tweets
Note: Consumers new to direct E-commerce posted on Twitter, sharing their impressions such as "recently * saw Tweets on direct E-commerce in my timeline" and "I was able to ** successfully place an order for blueberries".

III　Result

1 Data Overview

The weekly number of Japanese Tweets related to direct E-commerce increased from March 2020 and peaked

April when Japanese government asked people to quarantine themselves and the state of emergency was announced. The average number of Tweets after April, 2020 increased about four times compared to the before. Consumer who had some trouble to buy agricultural products at traditional store during the emergency statement might turn to direct E-commerce. Also, some farmer who struggled to sell their agricultural product because of school closures and the request to close the restaurant might try to sell through direct E-commerce. Many companies supported them with the promotions like free shipping.

Table 2 Frequent Words (Top 20) Posted by "PM Producer" and "Other"

	PM Producer		Other		Total	
1	ポケマル PokeMaru	2,142 (46.3)	食べチョク TabeChoku	34,227 (43.7)	食べチョク TabeChoku	35,103 (42.3)
2	食べチョク TabeChoku	876 (18.9)	ポケマル PokeMaru	21,970 (28.0)	ポケマル PokeMaru	24,112 (29.1)
3	販売 Sale	492 (10.6)	生産者 Producer	10,451 (13.3)	生産者 Producer	10,808 (13.0)
4	ポケットマルシェ PocketMarche	487 (10.5)	ポケットマルシェ PocketMarche	8,777 (11.2)	ポケットマルシェ PocketMarche	9,264 (11.2)
5	農家 Farmer	415 (9.0)	農家 Farmer	8,629 (11.0)	農家 Farmer	9,044 (10.9)
6	出品 Sell	375 (8.1)	食べる Eat	8,293 (10.6)	食べる Eat	8,623 (10.4)
7	生産者 Producer	357 (7.7)	美味しい Delicious	7,654 (9.8)	美味しい Delicious	7,916 (9.5)
8	野菜 Vegetable	349 (7.5)	買う Buy	6,799 (8.7)	買う Buy	6,940 (8.4)
9	食べる Eat	330 (7.1)	届く Arrive	6,648 (8.5)	届く Arrive	6,785 (8.2)
10	セット Set	318 (6.9)	野菜 Vegetable	5,789 (7.4)	野菜 Vegetable	6,138 (7.4)
11	注文 Order	279 (6.0)	食材 Foodstuff	5,280 (6.7)	食材 Foodstuff	5,380 (6.5)
12	美味しい Delicious	262 (5.7)	販売 Sale	4,622 (5.9)	販売 Sale	5,114 (6.2)
13	今年 ThisYear	253 (5.5)	注文 Order	4,437 (5.7)	注文 Order	4,716 (5.7)
14	人 People	243 (5.3)	購入 Purchase	4,429 (5.7)	購入 Purchase	4,545 (5.5)
15	発送 Shipping	243 (5.3)	直送 DirectShipping	4,408 (5.6)	直送 DirectShipping	4,491 (5.4)
16	月 Month	215 (4.6)	通販 HomeShopping	4,261 (5.4)	通販 HomeShopping	4,339 (5.2)
17	収穫 Harvest	193 (4.2)	漁師 Fisher	4,168 (5.3)	漁師 Fisher	4,276 (5.2)
18	良い Good	192 (4.2)	ネット Internet	4,109 (5.2)	ネット Internet	4,222 (5.1)
19	お願い Favour	188 (4.1)	産直 DirectMarketing	3,678 (4.7)	産直 DirectMarketing	3,772 (4.5)
20	作る Make/Grow	183 (4.0)	旬 in Season	3,494 (4.5)	旬 in Season	3,610 (4.4)
Tweets		4,624		78,353		82,977

Source: Collected Tweets
Note: Shaded cells represent unique words.

Table 3 Period and Coding Differences between "PM Producer" and "Other"

	Before	During	Emergency	AgrProd.	Livestock	Seafood	Organic	Support	Promotion	Positive	FirstExp	Total
PM Producer	662 (14.3)	3,025 (65.4)	937 (20.3)	593 (12.8)	134 (2.9)	348 (7.5)	35 (0.8)	29 (0.6)	229 (5.0)	734 (15.9)	371 (8.0)	4,624
Other	9,801 (12.5)	48,760 (62.2)	19,792 (25.3)	9,788 (12.5)	3,128 (4.0)	9,289 (11.9)	1,023 (1.3)	1,005 (1.3)	5,403 (6.9)	15,208 (19.4)	5,687 (7.3)	78,353
Total	10,463 (12.6)	51,785 (62.4)	20,729 (25.0)	10,381 (12.5)	3,262 (3.9)	9,637 (11.6)	1,058 (1.3)	1,034 (1.2)	5,632 (6.8)	10,235 (12.3)	6,785 (8.2)	82,977
Chi-square	12.786**	18.784**	57.891**	0.41	13.555**	79.304**	10.012**	14.717**	25.756**	34.944**	3.665	

Source: Collected Tweets
Note: ** indicates statistical significance at 1 percent level respectively.

2 Pocket Marche Producers and Others

This section presents the findings of the analysis conducted on the tweets shared by the producers of Pocket Marche, as previously described. There is the critical difference between Pocket Marche producer, "PM Producer" and others, "Other". "Other" mainly consists of consumers, with a minority being TabeChoku producers. Many "PM Producer" posted several Tweets, at least four Tweets, whereas more than 80% of "Other" posted three or less Tweets. This result suggests producer tweeted repeatedly about their own business and agricultural product.

Table 2, the list of the most frequently appearing words posted by "PM Producer" and "Other" highlights that "PM Producer" posted quite different Tweet from "Other" posted. They posted Tweets related to their sales including the words such as “出品(Sell)”, “セット(Set)”, “発送(Shipping)”, and “お願い(Favor)”, and their agriculture including the words such as “今年(This Year)”, “月(Month)” [1], “収穫(Harvest)”, and “作る(Make/Grow)”. Whereas, “Other” posted Tweets related to their order including the words like “届く(Arrive)”, “食材(Foodstuff)”, “直送(Direct Shipping)”, and “旬(in Season)”.

Chi-square test (Table 3) revealed the statistical differences between “PM Producer” and “Other”. “PM Producer” posted more than “Other” before COVID period. Meanwhile, “Other” posted more Tweet about organic product and promotion like free shipping and coupon. And they posted more positive Tweet and seemed to be willing to support farmer during COVID-19 pandemic.

Table 4 Frequent Words (Top 20) for Each Period

	Before	Emergency	During	Total
1	ポケマル 4,194 PokeMaru (40.1)	食べチョク 8,413 TabeChoku (40.6)	食べチョク 23,398 TabeChoku (45.2)	食べチョク 35,103 TabeChoku (42.3)
2	食べチョク 3,292 TabeChoku (31.5)	ポケマル 6,023 PokeMaru (29.1)	ポケマル 13,895 PokeMaru (26.8)	ポケマル 24,112 PokeMaru (29.1)
3	ポケットマルシェ 1,794 PocketMarche (17.1)	ポケットマルシェ 2,826 PocketMarche (13.6)	生産者 6,979 Producer (13.5)	生産者 10,808 Producer (13.0)
4	農家 1,277 Farmer (12.2)	生産者 2,722 Producer (13.1)	食べる 5,412 Eat (10.5)	ポケットマルシェ 9,264 PocketMarche (11.2)
5	生産者 1,107 Producer (10.6)	農家 2,493 Farmer (12.0)	農家 5,274 Farmer (10.2)	農家 9,044 Farmer (10.9)
6	野菜 1,042 Vegetable (10.0)	食べる 2,271 Eat (11.0)	美味しい 5,002 Delicious (9.7)	食べる 8,623 Eat (10.4)
7	食べる 940 Eat (9.0)	美味しい 2,213 Delicious (10.7)	ポケットマルシェ 4,644 PocketMarche (9.0)	美味しい 7,916 Delicious (9.5)
8	美味しい 701 Delicious (6.7)	買う 2,096 Buy (10.1)	届く 4,427 Arrive (8.5)	買う 6,940 Buy (8.4)
9	買う 643 Buy (6.1)	届く 1,824 Arrive (8.8)	買う 4,201 Buy (8.1)	届く 6,785 Arrive (8.2)
10	販売 543 Sale (5.2)	野菜 1,665 Vegetable (8.0)	食材 3,674 Foodstuff (7.1)	野菜 6,138 Vegetable (7.4)
11	届く 534 Arrive (5.1)	食材 1,323 Foodstuff (6.4)	販売 3,495 Sale (6.7)	食材 5,380 Foodstuff (6.5)
12	購入 466 Purchase (4.5)	直送 1,315 DirectShipping (6.3)	野菜 3,431 Vegetable (6.6)	販売 5,114 Sale (6.2)
13	人 463 People (4.4)	注文 1,306 Order (6.3)	注文 2,987 Order (5.8)	注文 4,716 Order (5.7)
14	作る 446 Make/Grow (4.3)	購入 1,279 Purchase (6.2)	通販 2,836 HomeShopping (5.5)	購入 4,545 Purchase (5.5)
15	嬉しい 435 Happy (4.2)	通販 1,256 HomeShopping (6.1)	購入 2,800 Purchase (5.4)	直送 4,491 DirectShipping (5.4)
16	消費者 430 Consumer (4.1)	漁師 1,243 Fisher (6.0)	漁師 2,799 Fisher (5.4)	通販 4,339 HomeShopping (5.2)
17	注文 423 Order (4.0)	ネット 1,212 Internet (5.8)	産直 2,794 DirectMarketing (5.4)	漁師 4,276 Fisher (5.2)
18	使う 405 Use (3.9)	販売 1,076 Sale (5.2)	直送 2,783 DirectShipping (5.4)	ネット 4,222 Internet (5.1)
19	直送 393 DirectShipping (3.8)	送料 1,027 ShippingFee (5.0)	ネット 2,705 Internet (5.2)	産直 3,772 DirectMarketing (4.5)
20	出品 387 Sell (3.7)	使う 1,018 Use (4.9)	旬 2,558 in Season (4.9)	旬 3,610 in Season (4.4)
Tweets	10,463	20,729	51,785	82,977

Source: Collected Tweets
Note: Shaded cells represent unique words.

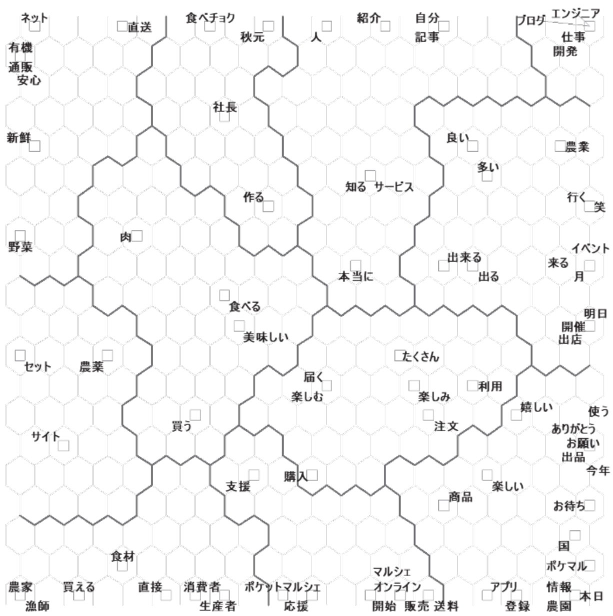

Fig. 1 SO Map before COVID-19 Pandemic
Source: Collected Tweets

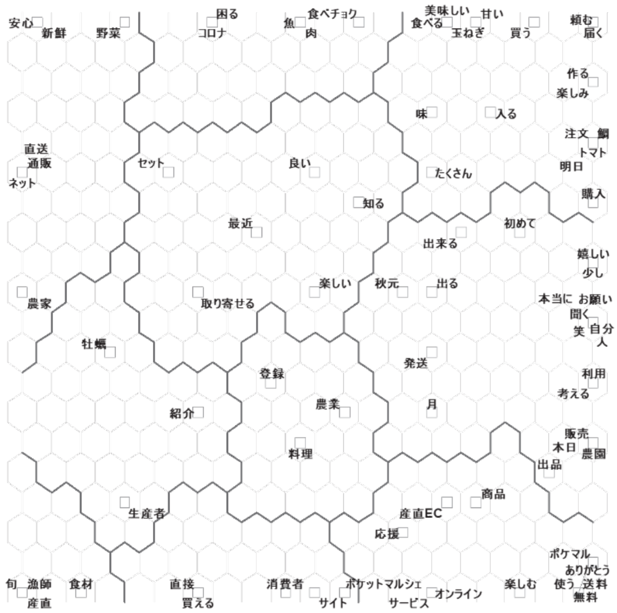

Fig. 2 SO Map at State of Emergency
Source: Collected Tweets

3 Before COVID, State of Emergency, and During COVID

Table 4 illustrates the differences of the frequently appearing words between the period, before COVID, state

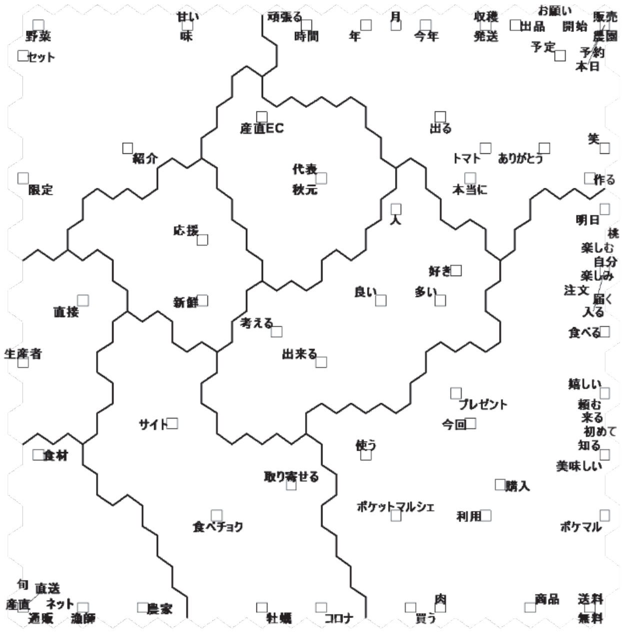

Fig. 3 SO Map during COVID-19 Pandemic

Source: Collected Tweets

of emergency, and during COVID. There are several unique words in before COVID period. The frequent words, “人(People)”, “作る(Make/Grow)”, and “出品(Sell)” also appeared in the list of “Producer” frequent words(Table 2). This suggests that producer is one of the main Twitter users related to direct E-commerce before COVID-19 pandemic. This means that direct E-commerce had not spread to consumer well before COVID-19 pandemic, but producer had felt “Happy(嬉しい)” about direct E-commerce.

Figure 1, 2 and 3 are the self-organizing maps of 80 frequent words with the 1,000 training steps in Tweets before COVID period, state of emergency and during COVID period. The number of clusters for each map were determined based on the agglomeration of the hierarchical cluster analysis. In these maps, words with similar co-occurrence patterns are located close to each other on the map. There are several words related to system engineer like “エンジニア(Engineer)”, “ブログ(Blog)”, “開発(Development)”, and “仕事(Work)” top right corner of figure 1. On the top left corner of figure 1, there are some words about organic farming like “有機(Organic)”, “野菜(Vegetable)”, “新鮮(Fresh)”, and “安心(Relief)”. These IT engineering and organic farming words reflect the situation that IT engineer and organic farmer (and their customer) are the main groups that were interested in direct E-commerce. But these words don’t appear on figure 2 and 3, after COVID-19 pandemic. This change reflects the spread of interesting on direct E-commerce to a broad spectrum consumers during COVID-19 pandemic. Whereas self-organizing map of before COVID period is unique, there are similarities between state of emergency map and during COVID period map. There is first experience and positive words cluster including “初めて(First Time)” and “嬉しい(Happy)” in both map. But these two clusters are slightly different. There are several words related to producer like “出品(Sell)”, “発送(Shipping)”, “お願い(Favor)”, and “月(Month)” in the cluster of Figure 2. On the other side, there are several words related to consumer like “購入(Purchase)”, “買う(Buy)”, and “届く(Arrive)” in the cluster of Figure 3. This difference suggests that producer or farmer had started direct E-commerce at the state of emergency and

Table 5 Coding Differences between Each Period

	Producer	Consumer	AgrProd.	Livestock	Seafood	Organic	Support	Promotion	Positive	FirstExp	Total
Before	1,295	534	1,056	271	516	326	170	504	1,792	656	10,463
	(12.4)	(5.1)	(10.1)	(2.6)	(4.9)	(3.1)	(1.6)	(4.8)	(17.1)	(6.3)	
Emergency	1,132	1,169	1,662	666	1,733	331	377	758	2,452	915	11,663
	(9.7)	(10.0)	(14.3)	(5.7)	(14.9)	(2.8)	(3.2)	(6.5)	(21.0)	(7.8)	
During	7,808	5,082	7,663	2,325	7,388	401	487	4,370	11,698	4,487	60,851
	(12.8)	(8.4)	(12.6)	(3.8)	(12.1)	(0.7)	(0.8)	(7.2)	(19.2)	(7.4)	
Total	10,235	6,785	10,381	3,262	9,637	1,058	1,034	5,632	15,942	6,058	82,977
	(12.3)	(8.2)	(12.5)	(3.9)	(11.6)	(1.3)	(1.2)	(6.8)	(19.2)	(7.3)	
Chi-square	88.433**	187.031**	88.508**	149.547**	591.248**	691.431**	484.398**	80.677**	53.975**	22.024**	

Source: Collected Tweets

Note: ** indicates statistical significance at 1 percent level respectively.

consumer had started it after that. There are also “送料無料(Free Shipping)” and “プレゼント(Free gift)” in the first experience cluster at Figure 3. This result means that the promotion like free shipping and free gift encouraged consumer to start direct E-commerce.

Chi-square test revealed the statistical differences between each period and supported three facts found in previous analysis (Table 5). First, direct E-commerce had been niche market related to organic product, according to the statistical difference of organic coding. Second, both producer and consumer had started to use direct E-commerce at state of emergency or during COVID period, according to the statistical difference of first experience coding. Third, there had been several sales promotions like free shipping and free gift during COVID period including state of emergency, and they had attracted consumers, according to the result of promotion coding differences.

1) “Producer” posted Tweets like, “I grew tomato this month.” or “I will have a good harvest this year.”

IV　Conclusion

This Twitter data analysis is useful to understand the impact of COVID-19 on direct E-commerce in Japan. Tweets per producers were much more than consumers. Producers tried to promote and sell their products and ask people to support them through direct E-commerce. Meanwhile consumers increased during state of emergency. They were willing to support farmers by buying from farmer directly, and also they had been attracted by free shipping and free gift. The implementation of promotional tactics such as free shipping and complimentary gifts is deemed necessary to facilitate the continued growth and expansion of the direct E-commerce market. Direct E-commerce skyrocketed under the state of emergency. Before that, direct E-commerce was a niche organic market. Many producers and consumers tried to use direct E-commerce during COVID period including state of emergency. Promotion like free shipping and free gift played significant role in widespread direct E-commerce.

This study contains some limitations. First, the key words to collect Tweets may have been incomplete. These key words should be extended to cover more Tweets related to direct E-commerce. Second, “Other” included TabeChoku producer. Some of them might be identified to improve these analyses with their Twitter profile descriptions. Finally, this study used only Twitter data. Further research should use other social media data such as Instagram and Facebook.

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