Public Response To Federal Electronic Cigarette Regulations Observed through the Lens of Social Media: Natural Language Processing and Topic Modeling

Shuo-Yu Lin, Sahithi Kiran Tulabandu, J. Randy Koch, Rashelle B. Hayes, Andrew J. Barnes, Hemant Purohit, Songqing Chen, Bo Han, Hong Xue

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Table of Contents

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Abstract

Background: E-cigarette use has been a public health issue in the US. On June 23, 2022, the FDA issued marketing denial orders (MDOs) to Juul Labs Inc. for all of their products currently marketed in the United States. However, one day later, on June 24, 2022, a federal appeals court granted a temporary reprieve to Juul Labs that allowed it to keep its e-cigarettes on the market. As the conversation around Juul continues to evolve, it is crucial to gain insights into the sentiments and opinions expressed by individuals on social media

Objective: To better understand the response of the general public to the policy, and the life-cycle of public health-related policy on social media.

Methods: 6,023 tweets and 22,288 reply/retweets were collected from Twitter (rebrand as X) between Jun 2022 and October 2022. We conducted a descriptive analysis, topic modelling utilizing the state-of-the-art BERTopic technique, and sentiment analysis.

Results: We found that the life cycle of reactions to the FDA's ban on Juul lasted no longer than a week on Twitter. Not only the news related to the announcement itself but the surrounding discussions (the 6 topics presented in the study) diminished shortly after June 23rd, 2022—the date when the ban was officially announced. Of the top 50 most retweeted tweets, we found posters responded from neutral (23/45, 51.11%) to more negatively (19/45, 42.22%) on the corresponding topics.

Conclusions: We observed a short life-cycle for this news announcement with more negative sentiment toward the FDA's ban on JUUL. Policymakers could employ tactics such as ongoing updates and reminders about the ban, highlighting its impact on public health, and actively engaging with influential social media users who can help sustain the conversation.

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Abstract

Background

E-cigarette use has been a public health issue in the US. On June 23, 2022, the FDA issued marketing denial orders (MDOs) to Juul Labs Inc. for all of their products currently marketed in the United States. However, one day later, on June 24, 2022, a federal appeals court granted a temporary reprieve to Juul Labs that allowed it to keep its e-cigarettes on the market. As the conversation around Juul continues to evolve, it is crucial to gain insights into the sentiments and opinions expressed by individuals on social media

Objective

To conduct a comprehensive analysis of tweets before and after the ban on Juul, aiming to shed light on public perceptions and sentiments surrounding this contentious topic, and to better understand the life-cycle of public health-related policy on social media.

Methods

Natural language processing (NLP) techniques were utilized, including the state-of-the-art BERTopic topic modeling and sentiment analysis. 6,023 tweets and 22,288 reply/retweets were collected from Twitter (rebranded as X) between June 2022 and October 2022. The encoded topics were used in time-trend analysis to depict the boom and bust cycle; Content analyses of retweets were also performed to better understand public perceptions and sentiments of this contentious topic.

Results

The attention surrounding the FDA's ban on Juul lasted no longer than a week on Twitter. Not only the news (i.e., Tweets with a YouTube link that directs to the news site) related to the announcement itself but the surrounding discussions (e.g., potential consequences of this ban/block and concerns toward kids/youth health) diminished shortly after June 23, 2022—the date when the ban was officially announced. Although a short rebound was observed on July 4th ,2022 that was contributed by the suspension on the following day, discussions dried out in two days. Of the top 50 most retweeted tweets, we observed that, except for neutral (23/45, 51.11%) sentiment that broadcasted the announcement, posters responded more negatively (19/45, 42.22%) on the FDA's ban.

Conclusion

We observed a short life-cycle for this news announcement, with a preponderance of negative sentiment toward the FDA's ban on JUUL. Policymakers could employ tactics such as issuing ongoing updates and reminders about the ban, highlighting its impact on public health, and actively engaging with influential social media users who can help sustain the conversation.

Keywords

Public Health, E-cigarette regulation, Social media, Data mining, Natural language, Topic modeling

I. Introduction

E-cigarette use has been a public health issue in the U.S. Its prevalence increased among adults from 1.4% in 2014 to 6.4% in 2021, primarily owing to an increase among those who had never smoked cigarettes [1, 2]. The upward trend was significantly higher later in the COVID-19 pandemic (April 2021–April 2022) compared to its initial months (March–July 2020) [3]. In addition, e-cigarette use may serve as a behavioral marker of risk for mental health problems among youth, including potential depression and suicidal ideation [4, 5], as well as potential pathological changes in their oral and respiratory systems [6].

Juul, who once owned a majority market share of e-cigarette sales, has garnered significant attention and controversy due to the widespread use of its products, especially among young people, and their potential health risks [7, 8]. Concerns were raised by state and federal investigators, and it was determined that Juul executives knew their marketing contributed to skyrocketing youth vaping rates nationwide, reversing years of tobacco control efforts [9, 10]. According to the Food and Drug Administration (FDA), nearly 10.7 million young people from 12-17 years old have used e-cigarettes or are open to trying them [11]. After reviewing the company's premarket tobacco product applications, the U.S. FDA determined that the application lacked sufficient evidence regarding the toxicological profile, raising public health concerns [12]. On June 23, 2022, the FDA issued marketing denial orders (MDOs) to Juul Labs Inc. for all of their products currently marketed in the United States [12]. However, one day later, on June 24, 2022, a federal appeals court granted a temporary reprieve to Juul Labs that allowed it to keep its e-cigarettes on the market [13]. On July 5, 2022, the FDA administratively stayed the marketing denial order. This administrative stay temporarily suspends the order during the additional review but does not rescind it [12].

From the policymaker's point of view, as the conversation around Juul continues to evolve, it is crucial to gain insights into the sentiments and opinions expressed by individuals on social media platforms like Twitter (rebranded as X on July 23, 2023). Understanding public opinions as well as the life cycle of an important policy announcement that moves the needle of public perceptions can better position the government to facilitate public awareness and curb miscommunication in a resource-constrained environment.

Traditionally, the way to gather responses from the general public relies on large public surveys or small focus group discussions. It was not until recently that copious amounts of unstructured text data on social media could be processed, analyzed, and reasoned, all with the help of Natural Language Processing (NLP) techniques—methods that integrate computer science, artificial intelligence, and computational linguistics. Over the past several years, there have been innovations in the NLP research that resonate in public health and social media research [14]. More importantly, recent applications have started to adopt a cutting-edge pre-training of deep bidirectional transformers for language understanding (BERT) approach that transforms NLP tasks. NLP pipelines have been intensively developed for a variety of text-processing problems—topic modeling, text summarization, and sentiment analysis [15]. In the present study, we utilize these NLP techniques to delve into the social media data on e-cigarettes, allowing us to better understand the response of the general public to the evolving policy issues and the life-cycle of public health-related policy concern expressed on social media. We conduct comprehensive analysis of tweets before and after the ban on Juul, aiming to shed light on public perceptions and sentiments surrounding this contentious topic.

II. Methods

We collected Twitter posts, responses, and retweets related to the FDA's ban on JUUL between June 2022 and October 2022. Keywords used for searching include “FDA,” “Ban,” “JUUL,” and “e-cigarettes,” and combinations of these four. We used Twitter official Academic API V2, which has been shown to create almost complete samples of Twitter data [16]. Four data sets were obtained from Twitter for further processing: (1) The master file that contains Twitter post text, associated post identifier, and reply. (2) The post-metric file that contains public metrics, including count of retweets, replies, likes, and quotes. (3) The author-metric file that contains author (tweet poster) metrics, including numbers of followers, following, tweets previously posted, and listed. (4) The entity file, which indicates the potential entity that posters are affiliated with. We removed duplicates and kept each post that had only one observation in the master file. We then performed one-to-one merges between the master file and the remaining three subsets. In total, we obtained 6,023 tweets and 22,288 replies/comments and retweets.

Not only did we collect text and emoji from these posts and responses, we also collected information regarding the date/time when posts and comments were created, as well as metrics associated with a post (i.e., counts of retweets, replies, likes, and quotes) at the time of data collection. In addition, we also collected user metrics such as the number of followers a poster has, the number of accounts a poster follows, the number of tweets an author has posted from the time the account was established, and the number of publicly listed organizations of which the user is a member.

In the present study, we conducted a descriptive analysis, topic modeling utilizing the state-of-the-art BERTopic technique, and sentiment analysis.

In the descriptive analysis we described the number of posts during the observational period to give readers an idea of how long the life cycle of “FDA’s ban on JUUL” lasted. We separated the time period into three sections: before Jun 23, 2022, between Jun 23, 2022 and July 5, 2022, and after July 5, 2022, reflecting the fact that this ban was suspended on July 05. We counted the total number of tweets and retweets, and we recorded the selected topics over time.

For topic modeling analysis, traditionally, the field has been dominated by the Latent Dirichlet Allocation (LDA) model [17]. One limitation of this model is that through bag-of-words representations, it disregards semantic relationships among words. As these representations do not account for the context of words in a sentence, the bag-of-words input may fail to accurately represent documents. The BERTopic is an emerging topic modeling network that simplifies the topic-building process. There are various elements to model these topics. In the present study five procedures are processed:

(1) Embedding, where documents are converted into numerical representatives. The sentence transformer used here is all-MiniLM-L6-v2, a pre-trained monolingual model that compresses large transformers simply and effectively [18].

(2) Dimension reduction of the input embeddings. We use the default Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) [19]. UMAP is a fuzzy topological structure-based dimension reduction technique that is used to reduce the complexity of data set by reducing the number of features while keeping the most important properties of the original data. The default parameters were used (i.e., 15 neighbors and 5 components with zero minimum distance)

(3) Clustering after the dimension reduction of the input embeddings, i.e., similar embeddings were clustered into groups to extract topics. The clustering is a key to the accuracy of topic representations. Here we used the HDBSCAN, a hierarchical clustering algorithm [20], to group the input embeddings into distinct clusters based on a user-specified fine-tuned cluster size (set to 15 as a default). These clusters are rudimentary representation of potential topics. More default fine-tunning parameters were used (see the two repositories for more information [21, 22]). The stable clusters were extracted from the condensed tree.

(4) c-TF-IDF to get an accurate representation of the topic from bag-of-words that was generated from the previous steps. c-TF-IDF is used and takes into account what makes the

documents in one cluster different from documents in another cluster, and the importance score per word is calculated. The score is used to determine the presence and order within each topic that a user specifies[22].

In sentiment analysis, we analyzed the sentiments toward the ban (positive, negative, and neutral) of the most commonly outlined messages formulated in the tweets based on the topics generated from topic modeling. We constructed sentiment scores using VADER (Valence Aware Dictionary and Sentiment Reasoner) algorithms. VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media [23]. The score is computed by summing the valence scores of each word in the lexicon, adjusted according to the grammatical and syntactical conventions that humans use when expressing or emphasizing sentiment intensity, and then normalized to be between –1 (most extreme negative) and +1 (most extreme positive) [24]. Following the literature, we set standardized thresholds to classify sentences as either positive (normalized score ≧ 0.05), neutral (–0.05 <normalized score <0.05), or negative (normalized score ≦ –0.05) [23]. We selected the top 50 most-retweeted tweets to perform content analysis and sentiment analysis. The reason we chose the top 50 is because of the skewed distribution. Of all the tweets included, those with 22 or more retweets are in the 99th percentile (mean retweets being 1.69 with a 20.34 standard variation). The top 50 tweets we selected are those that were most popular, with retweet counts in the 99th percentile. Two coders manually coded the theme for each post separately, with kappa ranging from 0.25 to 0.89. All the analysis was conducted in Python 3.6 [25].

Ethical considerations

This study was exempted from institutional review broad approval because data provided by Twitter academic API are publicly available and deidentified.

III. Results

As can be seen in Table 1, between June 23 and July 05, the mean (SD) retweet count was 1.47 (17.85), with a higher count before June 23 (5.81 [46.41]) and a lower count after July 05 (0.75 [3.17]). (More in-depth analysis can be found in Table 2.) Similarly, the mean (SD) reply count was highest before June 23 (1.98 [12.07]) and lowest after July 05 (0.38 [1.87]), with a mean (SD) of 0.82 (10.39) until the end of the observational period (October 22, 2022). The mean (SD) like count was 9.58 (304.64) during the period of interest, with a higher count before June 23 (37.57 [384.17]) and a lower count after July 05 (2.35 [11.74]). Regarding author metrics, the mean (SD) number of followers was highest after July 05 (366,305 [2,344,692]) and lowest before June 23 (143,546 [1,043,550]), with a mean (SD) of 229,253 (1,825,307) across the entire sample. The mean (SD) number of accounts followed was highest before June 23 (2707 [13,995]) and lowest after July 05 (2061 [6,605]), with a mean (SD) of 2508 (14,059) across the entire sample.

Table 1: Summary statistics

	Timestamps			
	Total N = 6,023	Before Jun 23 N = 539	Between June 23 and July 05 N = 4,109	After July 05 N = 1,375
Post metrics				
Retweet count	1.69 (20.34)	5.81 (46.41)	1.47 (17.85)	0.75 (3.17)

Reply count	0.82 (10.39)	1.98 (12.07)	0.82 (11.74)	0.38 (1.87)
Quote count	0.76 (24.60)	3.92 (73.05)	0.56 (13.66)	0.12 (0.67)
Like count	10.44 (276.78)	37.57 (384.17)	9.58 (304.64)	2.35 (11.74)
Author matrices				
Author followers count	22,9253 (1,825,307)	143,546 (1,043,550)	194,634 (1,701,244)	366,305 (2,344,692)
Author following count	2,508 (14,059)	2,707 (13,995)	2,632 (15,793)	2,061 (6,605)
Author listed count	1,575 (10,057)	1,115 (6,412)	1,314 (8,877)	2,534 (13,800)
Author tweet count	141,171 (269,747)	99,475 (175,178)	139,556 (271,059)	162,345 (293,400)

Figure 1 presents the time trend analysis of all tweets related to the FDA's ban on Juul. Panel A plots tweets between June 23 and July 5—the pre-suspension period, while Panel B plots the period after July 5—the post-suspension period. The number of tweets and retweets associated with the FDA's ban experienced a significant decline between June 23 and June 26. On June 26, the quantity of posts experienced a significant decline, with only about 200 tweets compared to 5,000 posts on June 23. Panel A shows the tweets followed by a further decline until July 5th. The peak number of tweets related to the suspension of the FDA ban on JUUL (Panel B), which reached approximately 310, was observed on July 5th. The number of posts dropped subsequently, down to around 25 by July 08. Tweets and retweets associated with the suspension were not observed from July 09 to July 11. A slight increase in posts was noticed on July 12, but then wound down to null until the end of the observation period.

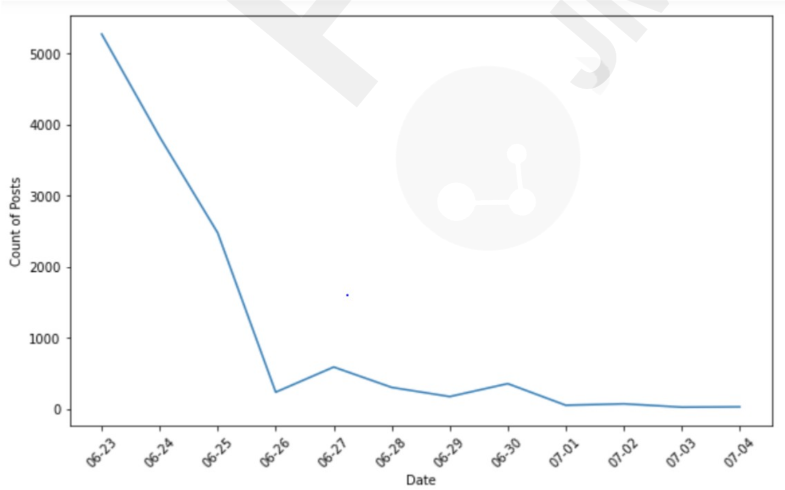


Figure 1 Panel A: The sharp decline of Tweets associated with FDA's ban. The blue line represents the trend of the number of Tweets and retweets associated with the FDA's initial ban announcement on 06-23-2022 up to the date of its suspension on 07-05-2022. The number of tweets and retweets associated with the FDA's ban experienced a significant decline between June 23 and June 26. On

June 26, the quantity of posts experienced a significant decline, with only about 200 tweets compared to 5,000 posts on June 23.

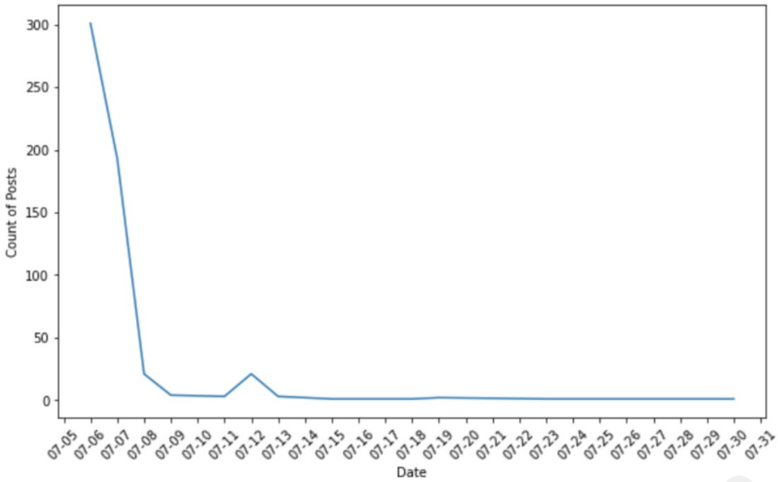


Figure 1 Panel B: The sharp decline of Tweets associated with the suspension of the FDA's ban. The blue line represents the trend of the number of Tweets associated with the suspension of the FDA's ban announced on July 5, 2022 to the end of July 31, 2022. On July 5th, we observed approximately 310 tweets related to the suspension of the FDA's ban on JUUL, the number of posts dropped subsequently, down to around 25 by July 08. Tweets and retweets associated with the suspension were not observed from July 09 to July 11. A slight increase in posts was noticed on July 12, but then wound down to null until the end of the observation period.

Figure 2 presents the life-cycle of the top 6 most popular topics among the tweets related to the FDA's ban on Juul. These 6 topics were chosen because they are most inclusive and concise (see supplementary material Figure a1 for a detailed inter-topic distance map). The topics mentioned most frequently in all collected tweets, in rank order, are: (1) Tweets containing the FDA's ban on Juul with a YouTube link to a news media site or other relevant video content, as in the two examples below:

> *"Prof. Peter Pitts talks about the reported upcoming FDA ban on Juul with... https://t.co/8fW2Bf31Ct via @YouTube."*

The link above directs viewers to a news show talking about the FDA's ban on Juul (see Figure 3.a).

> *"FDA Expected To Ban Juul Products https://t.co/m2MGiGpER2 via @YouTube"*

The link in this quote directs viewers to NBC News (see Figure 3.b).

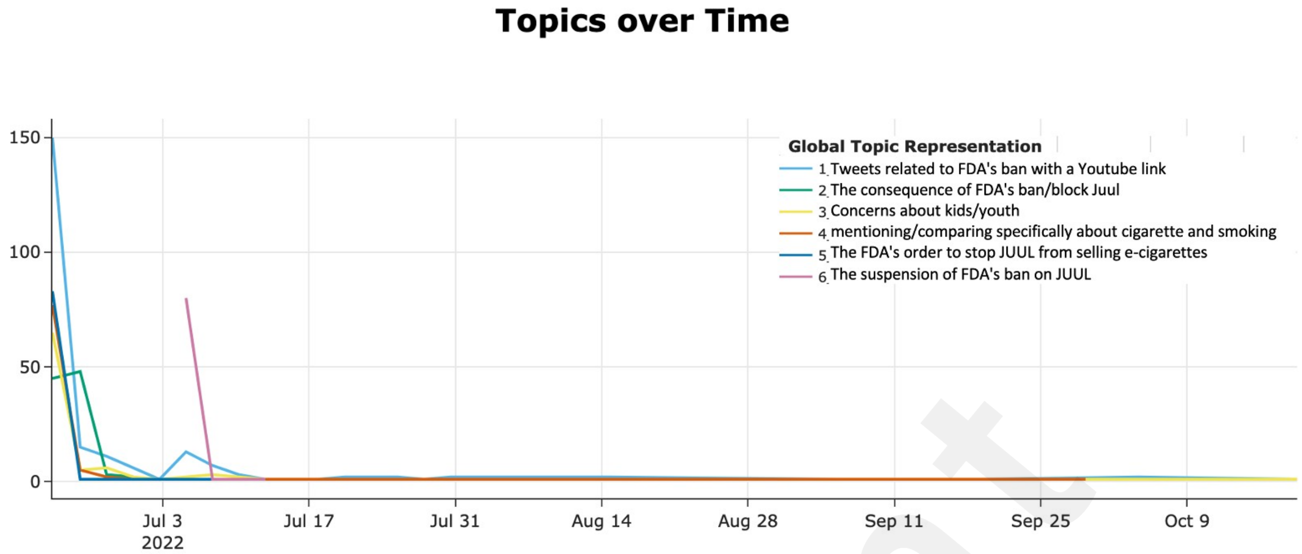
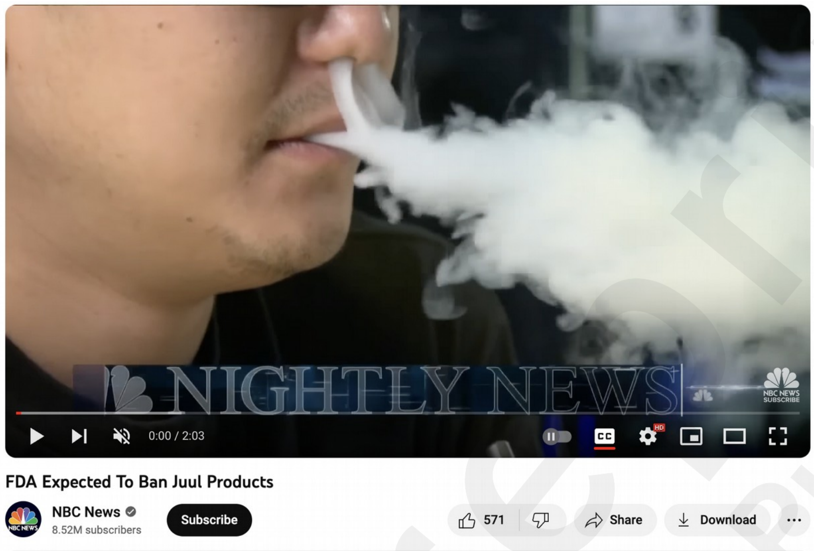


Figure 2: The life-cycle of the top 6 topics. The colored lines represent the number of tweets for each selected topic. The Y-axis represents the number of tweets. All topics experienced a peak on the date of the FDA policy announcement and a significant decline in the following week. We observed a short rebound for Topic 1 (tweets related to the FDA's ban with a YouTube news link) on July 4th, right before the announcement of suspension of the FDA's ban. The rebound on the number of tweets for Topic 1 diminished quickly, followed by a peak for Topic 6 (the suspension of the FDA's ban on JUUL). The life-cycle of Topic 6, however, was similar to other topics in that it faded out within a day or two.

(2) Tweets talking about the consequence of a continuous ban or block on JUUL. (3) Tweets related to concerns about kids and youth. (4) Tweets mentioning cigarettes and smoking. (5) Tweets that restated the FDA's order to stop Juul from selling e-cigarettes. (6) Tweets associated with the suspension of the FDA's ban on Juul. More concrete examples of word clouds are provided in supplementary material (Figures a2 and a3).

We observed interesting patterns in the frequency of the six different topics between June 23rd and Oct 9th. Specifically, we found that Topic 1 to Topic 5 experienced a peak in frequency on June 23rd with a maximum of 150 tweets, followed by a sharp decline. By July 5th the frequency of topics other than the suspension of the FDA's ban on JUUL were down to near null. We observed a short rebound for Topic 1 (tweets related to the FDA's ban with a YouTube news link) on July 4th, right before the announcement of suspension of the FDA's ban. The rebound on the number of tweets for Topic 1 diminished quickly, followed by a peak for Topic 6 (the suspension of the FDA's ban on JUUL). The life-cycle of Topic 6, however, was similar to other topics in that it faded out within a day or two.

(Panel A)



(Panel B)

Figure 3: YouTube links from example posts. The two screenshots represent external news media sites on YouTube from Tweets containing comments on the FDA's ban on Juul. The tweet linked with Panel A is *"Prof. Peter Pitts talks about the reported upcoming FDA ban on Juul with... https://t.co/8fW2Bf31Ct via @YouTube.* The tweet linked with Panel B is *"FDA Expected To Ban Juul Products https://t.co/m2MGiGpER2 via @YouTube"*

Table 2 shows the result of the content analysis. In the present study, we conducted the conceptual analysis, which determines the existence and frequency of concepts in Twitter text. We developed two sentiment concepts, two objective facts, and five topics. The two sentiment concepts are (1) sentiment of Twitter posts, and (2) whether the author of Twitter posts supports the FDA's ban on e-cigarettes. The two objective facts are (1) whether the post is directly tweeted or feeds from news, and (2) whether the post has an URL/link attached. The five topics are (1) related specifically to tobacco, nicotine, cigarettes, or smoking, (2) concerns of kids/youth, (3) the consequence of the FDA's ban or block on JUUL, (4) the suspension of the FDA's ban, and (5) the FDA's expected move with a YouTube news link. The raw agreements of these concepts ranged from 66% to 96%, with Kappa agreement statistics being significant ($p < 0.05$) except for one topic. We found, among the top 50 retweeted posts with a two-interrater agreement of between 66% to 96%, that 23 authors (23/45, 51.11%) expressed a neutral opinion on the FDA's ban on JUUL (most of these retweets were redirected from the FDA's official announcement or a news channel). 19 authors (19/45, 42.22%) opposed the ban, and 3 (3/45, 6.67%) authors supported the FDA's ban on JUUL. 27.27% (n = 9/33) of posts were directly tweeted or retweeted from a news agency. The sentiment of Twitter posts (generated by the machine learning models), similar to the authors' supportiveness (measured and verified by two independent coders), concentrated toward the neutral (n = 21/42, 50%) and negative (n = 19/42, 45.24%).

Table 2: Content and sentiment analysis

	Expected					Sentiment analysis			
Agreement	Agreement	Kappa	Std. Err.	Z	Prob>Z	Positive or Yes	Negative or No	Neutral	Topics
92.00%	44.72%	0.86	0.12	7.03	0	3	19	23	Whether author supports the FDA's ban
80.00%	44.60%	0.64	0.12	5.25	0	2	19	21	The sentiment of Twitter post
66.00%	54.48%	0.25	0.14	1.79	0.04	9	24	x	Directed tweeted or feeds from news
76.00%	65.68%	0.30	0.14	2.13	0.02	5	32	x	Topic: mentioning/comparing specifically about tobacco, nicotine, cigarettes
88.00%	81.92%	0.34	0.14	2.44	0.01	2	40	x	Topic: Concerns about kids/youth
66.00%	52.40%	0.29	0.14	2.02	0.02	11	21	x	Topic: the consequence of FDA's ban/block Juul
90.00%	74.48%	0.61	0.14	4.31	0	5	38	x	Topic: The suspension of FDA's ban
88.00%	88.00%	0.00					44	x	Topic: FDA's Expected move with @youtube news link (Y/N)
96.00%	63.52%	0.89	0.14	6.3	0	38	12	x	With URL

Notes: Sentiment analysis numbers reflect both coders' agreement.

Of the five topics generated by topic modeling, 34.38% (11/32) related to the consequence of the FDA's ban or block on JUUL; 13.51% (5/37) mentioned or compared e-cigarettes with tobacco, nicotine, cigarettes, or smoking; 11.63% (5/43) talked about the suspension of the FDA's ban; and 4.76% (4/42) concerned the use of e-cigarettes among kids/youth. Although many other posts in the 6,000 tweets were attached to a YouTube link, none of the top 50 posts provided such a link.

IV: Discussion

In the present study, we found that the life cycle of reactions to the FDA's ban on Juul lasted no longer than a week on Twitter. Not only the news related to the announcement itself but the surrounding discussions (the 6 topics presented in the study) diminished shortly after June 23, 2022—the date when the ban was officially announced. Of the top 50 most-retweeted tweets, we found posters responded more negatively on the corresponding topics.

Principal Findings

Our trend analysis findings reveal a pattern commonly observed in the life-cycle of online news. Our research shows a sharp increase in Twitter discussions surrounding the FDA's ban on Juul when the announcement was made on June 23, 2022, followed by a rapid decline in three days. The patterns for various specific topics were very similar to the general trend. Other Twitter-based studies focusing on the FDA's drug safety communication messaging about Zolpidem (a sedative-hypnotics used for sleeping problems) and on antibiotics found that daily mention in Twitter posts spiked at the time of official announcements on these topics, reaching maximal activity within 24 hours and returning to pre-peak basal levels within 48 hours [26, 27]. The sharp increase in engagement is not sustained. This pattern aligns with previous literature on the topic, which has documented the short attention span required and fast-paced nature of online discourse [28, 29]. The initial surge of interest and subsequent decline can be attributed to the fleeting nature of trending topics and the constant influx of new information competing for users' attention [30].

Although sharing a common pattern of short life-cycle, differences among topics warrant a further dissection. First, concern about kids and youth health is one of the most popular topics associated with the FDA's JUUL ban. The discussions surrounding the topic echo the growing body of evidence showing the adverse health effects of e-cigarettes on the younger population [31, 32]. Second, the potential consequence of the ban, as a categorized topic, sparked a more sustained discussion for two days after the announcement (Topic 2, green line shown in Figure 2).

Providing online space for people to reason and debate, rather than simply preaching facts could be a way to increase user engagement. For example, governments can partner with social media influencers that actively manage and encourage debates about important public health policies. This could not only increase the reach of information but also alter potential miscommunication on social media. Ongoing reminders about the ban could be another way to extend the duration of public engagement. Evidence showed that a reminder system on social media could enhance medical adherence to the treatment of commutable diseases [33]. We observed a short rebound of discussions about the FDA's ban with a YouTube news link on July 4th, right before the announcement of the suspension of the FDA's ban, indicating that timely reminders may be able to prolong user engagement.

Regarding sentiment, we found that of the top 50 retweeted posts, more than half were neutral regarding the ban (where the announcement was directly retweeted/posted), while 42% opposed the ban. We observed that Twitter users tended to be more negative toward the public health policies. The distribution of sentiments shows great similarity with attitudes toward other U.S. tobacco control laws. For example, a study focused on the Tobacco 21 law found that 42.4% of tweets opposed Tobacco 21, and 42.6% neither supported nor opposed the law [34]. The proportionally higher opposition is consistent with previous literature focusing on other social media sites. It has been shown that Facebook users are more likely to engage with negatively-framed anti-tobacco campaign posts [24]. On Twitter, research suggests that positive sentiment has dominated the discourse surrounding e-cigarettes [35]. Such positive sentiments were raised by e-cigarette advocates, along with nudging tactics, to communicate their beliefs. Positive sentiment about use of JUUL suggests that the product is being normalized among young people [36]. The positive attitude toward e-cigarettes forms a feedback-loop that could disseminate to ordinary people, making them more suspicious and more likely to hold negative opinions toward vaping-related policies [35].

In fact, similar public responses were observed in previous e-cigarette-related policies. On January 2, 2020, the FDA released the electronic cigarette (e-cigarette) flavor enforcement policy to prohibit the sale of all flavored cartridge–based e-cigarettes [37]. The proportion of negative sentiment tweets about e-cigarettes significantly increased after the announcement of this FDA policy compared with before the announcement of the policy [37]. Similar negative sentiments were found when New York state banned flavored e-cigarettes [38] as well as in public response to a social media tobacco prevention campaign [39].

When looking into topics more specifically, those twitter authors who hold negative opinions are mostly individual influencers. For example, the second, fourth, and ninth most retweeted tweets stated:

> *"Honestly crazy as that the FDA decided to ban Juul pods before banning actual cigarettes, the agenda obviously isn't just public health"*
>
> *" So the FDA wants to ban JUUL e-cigarettes for adults, but approved experimental mRNA vaccines for 6 month old infants at ~0% risk of having any complications from COVID?"*
>
> *"The WSJ reports that the FDA will ban Juul e-cigarettes tomorrow.*
> *Bad idea. E-cigarettes save lives"*

This pattern is similar to what was found in public reactions to other e-cigarette regulations on Twitter. Lazard and colleagues found all eight top influencers identified were actively against the FDA deeming of e-cigarettes—of which seven of them are individual consumers and proponents [40]—resulting in miscommunication. Miscommunication of tobacco control policy on social media sites had been documented. For example, many news tweets about the U.S. federal Tobacco 21 law—a sales law—incorrectly described the law as a purchase law, and some doubted its ability to limit youth access to tobacco products [41]. In addition, our selected example of the most retweeted tweets with negative sentiment showed that people often questioned the identity of the targeted groups, the intention of the authorities, and the effectiveness of the rules. This is consistent with previous research focusing on the FDA's action to prohibit menthol. It suggested that the tweets with a negative attitude questioned the FDA's proposed menthol cigarette rules from several angles, from the effectiveness of the rules and the targeted groups to even the feasibility of their enforcement [42].

Empirical Contributions and Policy Implications

Our findings have important implications for policymakers aiming to prolong the life cycle of discussions and increase their reach. To extend the duration of public engagement, policymakers could employ tactics such as ongoing updates and reminders about the ban, highlighting its impact on public health, and actively engaging with influential social media users who can help sustain the conversation. Additionally, strategies used in other fields, such as marketing and entertainment, could be adapted to enhance the reach of the information. Leveraging storytelling techniques, creating compelling visuals, and employing interactive formats have proven effective in capturing and maintaining public attention [43, 44]. Finally, employing social media influencers that actively create cohesive communications could increase the reach of information and alter potential miscommunication on social media. It has been shown that the antitobacco messages had a significantly lower potential reach, received a lower proportion of impressions, and spent a lower proportion of money per message [45]. Utilizing social influencers as message sources is a key factor for message dissemination and sustention. Evidence suggests that campaigns that utilized social influencers as message sources generated a greater volume of tweets per day and broader reach per day. More importantly, the oppositional messages diminished over time, which indicates a decrease in miscommunications. By employing these tactics and strategies, policymakers can aim to foster sustained engagement and maximize the impact of policy announcements in the age of rapidly evolving online discourse.

Strengths and Limitations

Although we collected comprehensive tweets to disentangle the public response to the FDA's ban on Juul, several limitations are worth noting in the present study. First, the opinions we observed might not be generalizable to the entire public since the typical Twitter users are between 25 and 34 years old [46]. Second, our analyses were limited to the data collected using pre-specified keywords, which might not be exhaustively comprehensive. As a result, some public responses may not have been covered. Furthermore, the sentiment analysis did not include replies/comments to those tweets, which could result in neglecting some user sentiments. However, the number of responses were low and the chance of underestimating positive and overestimating negative sentiments are likely minimal. Future research should develop insights in sustaining the life-cycle of discussions and avoiding miscommunication. Specifically, the government agency and organizations could work with influencers to share more focused and nonjudgmental messaging about policy reasoning with fun experiences that resonate with the targeted audiences' interests and values.[47] Researchers should also develop bottom-up agent-based simulation models to develop more insight into how tobacco control policies are disseminated and received by the general publics under different social network structures.

V. Conclusions

In this observational study, we found that individual Twitter users—other than regular news media—hold more negative sentiment towards the FDA's ban on JUUL. Furthermore, we observed a short life-cycle for this news announcement. To extend the duration of public engagement, policymakers could employ tactics such as ongoing updates and reminders about the ban, highlighting its impact on public health, and actively engaging with influential social media users who can help sustain the conversation.

VI. Data Availability and disclosure

The data used in the present study are made available in the following URL https://drive.google.com/drive/folders/13Pv1v7sALey7QxSP5gtC17sDKe2aJZpv?usp=drive_link. The codes used for the analyses are available upon proper request to the authors. No generative AI was used in any portion of the manuscript writing.

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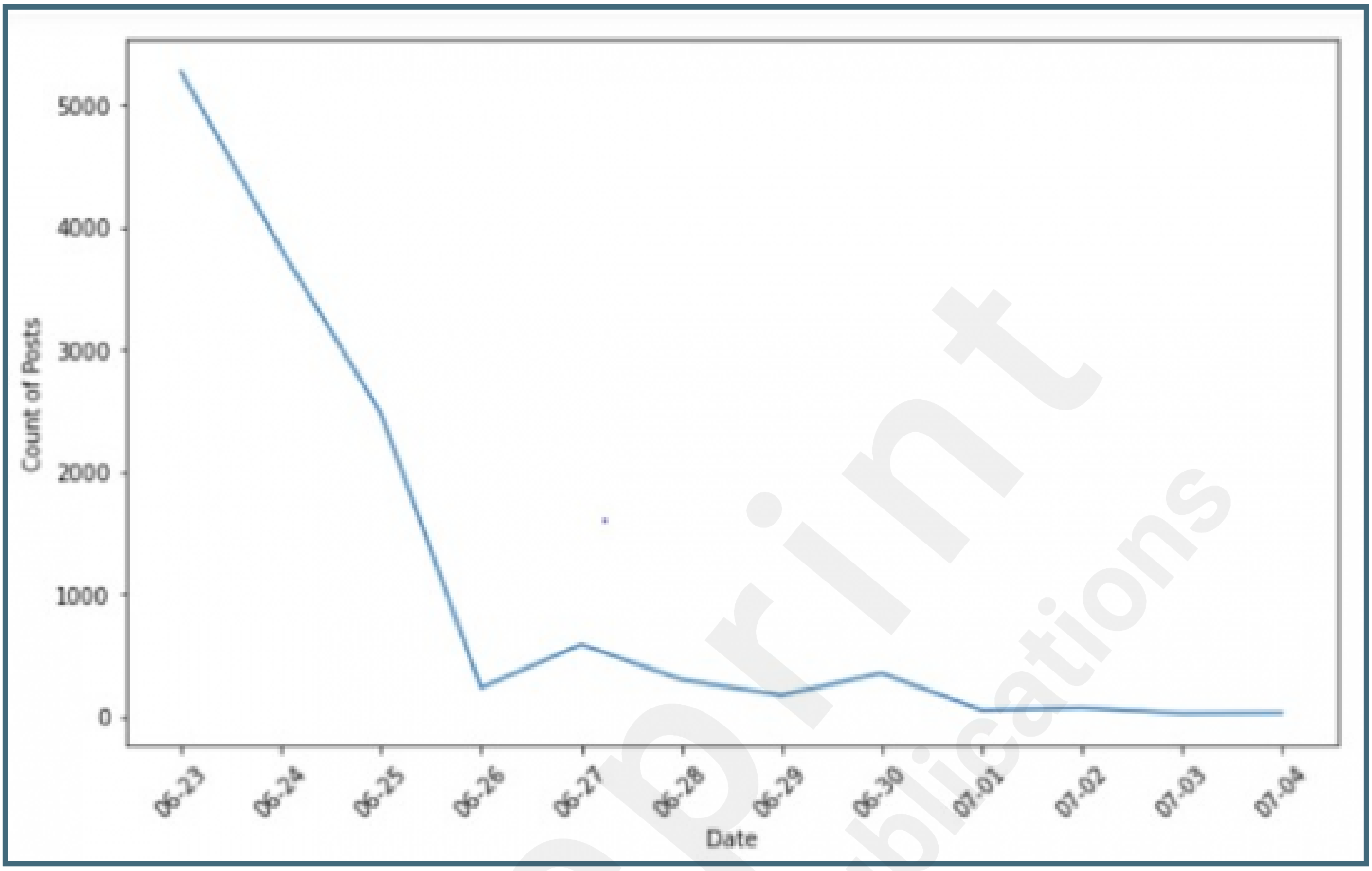
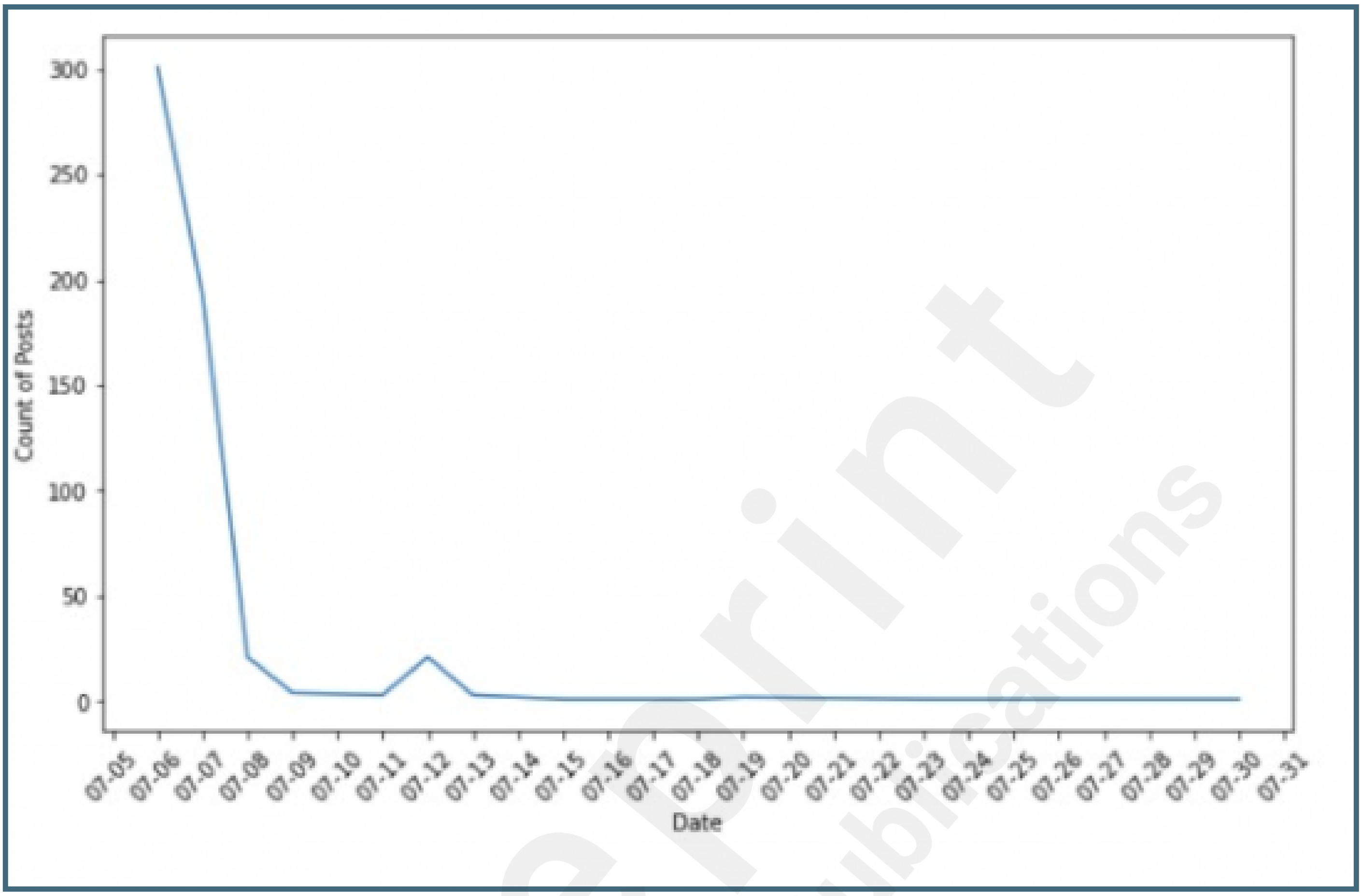
Supplementary Files

Figures

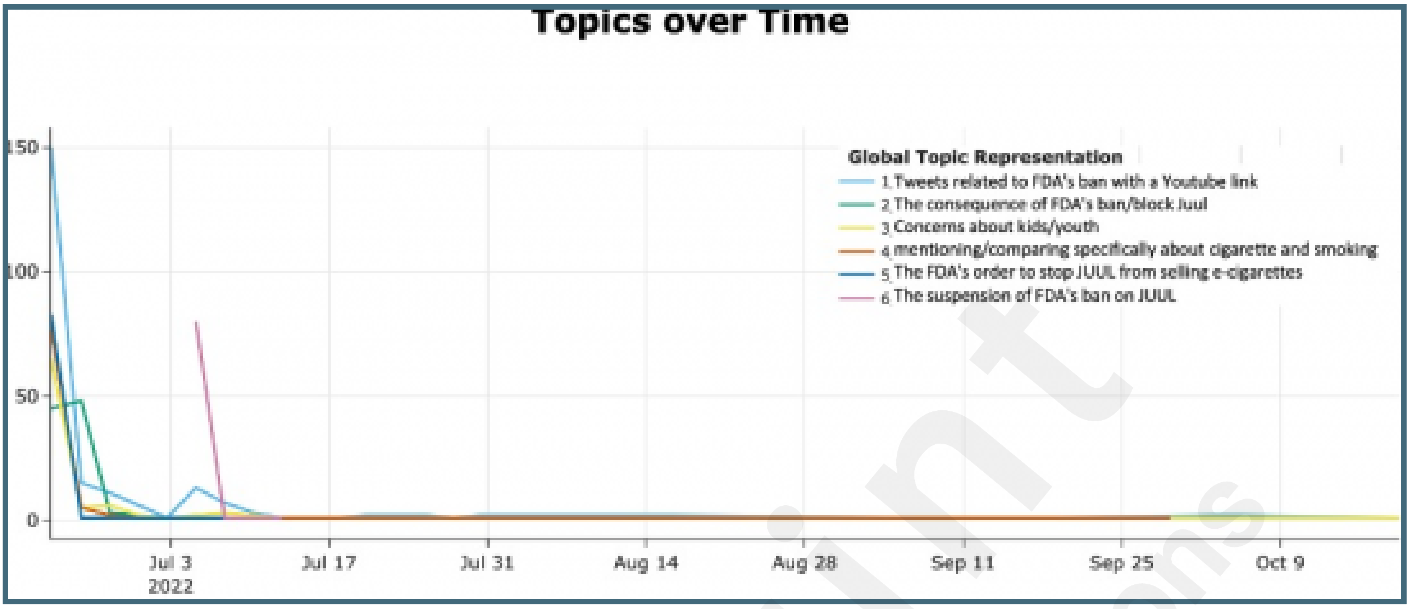
Trend of Tweets associated with FDA's Ban- 06/23 TO 07/05.



Trend of Tweets associated with the Suspension of FDA’s Ban-07/06-08/06.



The life-cycle of Top 6 topics.



Example posts with a Youtube link (panel A).

Example posts with a Youtube link (panel B).

Multimedia Appendixes

Untitled.
URL: http://asset.jmir.pub/assets/789c075b3ac0639284f7d8a623b4c53c.docx