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RESEARCH ARTICLE

E-Cigarette—Related Health Beliefs Expressed on Twitter Within the U.S.

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Introduction: This mixed-methods study analyzed English-language U.S.-based Twitter posts related to E-cigarette use from February 2021.

Methods: Posts were manually identified as health-related or not and, if health-related, whether they were posted by an E-cigarette user. A random selection of 1,000 health-related tweets from 986 unique E-cigarette users were qualitatively content analyzed for theory of planned behavior constructs as well as nature and tone of each tweet message. Using quantitative semantic network analysis, relationships among the identified topics and sentiment-specific conversation patterns were explored.

Results: The most salient health-related conversation topics of E-cigarette users, health beliefs corresponding to each theory of planned behavior construct, and major motivational contexts of E-cigarette use were identified. Seven topics emerged in positive tweets: smoking cessation, social impact generation, controls over addiction, therapeutic effects on physical and mental health, social support, device attachment, and peer influence. Nine topics emerged in negative tweets: side effects on physical health, vaping addiction, lack of E-cigarette regulations, peer pressure, increased risk of COVID-19, side effects on mental health, no help in smoking cessation, social conflict, and polysubstance use. Most assertions for E-cigarette benefits were not substantiated. Jokes in tweets appeared to contribute to the view of vaping as an attractive, enjoyable, safe, and fun activity. Discussions about positive aspects of E-cigarette use were concentrated on a few related topics, whereas tweets discouraging E-cigarette use presented a diverse, less related set of topics.

Conclusions: The results provide insights into the drivers of E-cigarette use behaviors. E-cigarette user perspectives gathered from social media may inform research to guide future prevention and cessation interventions.

INTRODUCTION

The use of battery-operated E-cigarettes, also known as vaping, has accelerated, with E-cigarette revenue reaching $13.6 billion in 2017 and being projected to generate $26.6 billion by 2025.[1,2] Although the long-term health effects are yet to be determined, several substances in electronic liquids may lead to further tobacco product

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2773-0654/$36.00
https://doi.org/10.1016/j.focus.2023.100067

use, cause various cancers and cardiovascular disease, and potentially harm brain development of youth and young adults.[3]

The theory of planned behavior (TPB) is a useful tool for understanding health behavior decisions, including smoking behaviors.[4] TPB uses 3 constructs to explain behavioral intentions: behavioral beliefs (attitudes), normative beliefs (subjective norms concerning the behavior), and control beliefs (perceived behavioral control). A favorable attitude and a supportive subjective norm provide motivation to engage in a behavior, but a concrete intention to do so is formed only when perceived control over the behavior is sufficiently strong.

Recent research has identified attitudes, norms, and behavioral controls that can encourage or discourage E-cigarette use on the basis of TPB.[5−8] Positive personal experiences with E-cigarette use, such as cheap prices,[9] led to favorable attitudes and increased E-cigarette use.[6−8] Many E-cigarette users believe that E-cigarettes are less harmful than conventional cigarettes[5,7,8]; however, people who use E-cigarettes to reduce or quit conventional cigarettes were less likely to consider quitting E-cigarettes.[5] Although these findings point to the importance of health beliefs in understanding E-cigarette use, previous research has typically been retrospective, including small, localized participant samples, and has not assessed all constructs of TPB.

Social media data can describe health beliefs of E-cigarette users in near real time and at low costs without instrument bias.[10] Social media offers online conversations that may encourage or discourage E-cigarette use by referencing a specific E-cigarette product or by conveying a casual attitude through jokes or memes about E-cigarettes. Similarly, social media messages can also express norms of approval or disapproval.[11] If health consequences associated with the behavior are notably severe, public concern sways toward disapproval of the behavior.[12,13] Norms can also be established or reinforced through social media conversations. For example, a study showed that prosmoking messages had a significant effect on adolescents' perceptions of peer norms for smoking.[14] Social media messages may reinforce the perceptions of normative behavior among those already exposed to E-cigarette use behaviors within their environment. Social media can be used as a resource for sharing and disseminating self-management and self-efficacy building information on health behaviors by enabling individuals to share and obtain knowledge and skills necessary to improve self-control behaviors.[15−18]

This paper identifies the most salient conversation topics in E-cigarette−related social media posts corresponding to each theoretical construct of TPB and analyzes the relationships between identified topics. We first performed a content analysis of E-cigarette users' Twitter posts. Of the various social media platforms, Twitter has become a popular means for marketing and sharing knowledge and beliefs about health topics, such as the promotion, distribution, and social acceptance of E-cigarettes among E-cigarette users.[19−28] Because most tweets are publicly available and easy to access, Twitter has become a rich data source for surveillance of public opinion about E-cigarettes, among other topics.[21,29−37] Next, we constructed sentiment-specific semantic networks of Twitter content. Semantic network analysis assumes that words that exist close to each other are likely related and classifies dialogue on the basis of co-occurrences of topics throughout the network of discussions on a subject of interest.[38] We posed the following research questions: (1) What behavioral, normative, and control beliefs are presented about E-cigarette use? (2) What specific beliefs surface most consistently across E-cigarette users? (c) How would behavioral, normative, and control beliefs toward E-cigarettes together explain behavioral intention?

METHODS

This study employed a mixed-methods approach that includes a qualitative content analysis and a quantitative sentiment-specific semantic network analysis of E-cigarette users' Twitter posts (Figure 1). The University of Southern California's IRB determined that no ethics approval was required for this study because the data are publicly available.

Study Sample

Publicly available *English language Twitter posts* (referred to as tweets) written in the U.S. between February 1, 2021 and February 28, 2021 were retrieved using search keywords. The period was based on a series of events beginning on November 25, 2020, when a study claimed to have found evidence of an increased susceptibility of vapers to coronavirus disease 2019 (COVID-19).[39] On December 27, 2020, Congress passed "The Preventing Online Sales of E-Cigarette to Children Act." Data collection began on February 1, 2021 to avoid the abnormal online conversation patterns during the New Year holiday season. Studies have reported extreme amounts of tweet volume and holiday events-related keyword frequency, whereas negative sentiment tweet percentages are lower than average during the Christmas and New Year holiday period (from mid-December to mid-January).[40−42] Tweets were retrieved through Twitter's application programming interface using *ecig.**, *vape*, or *vaping* and 2 most popular

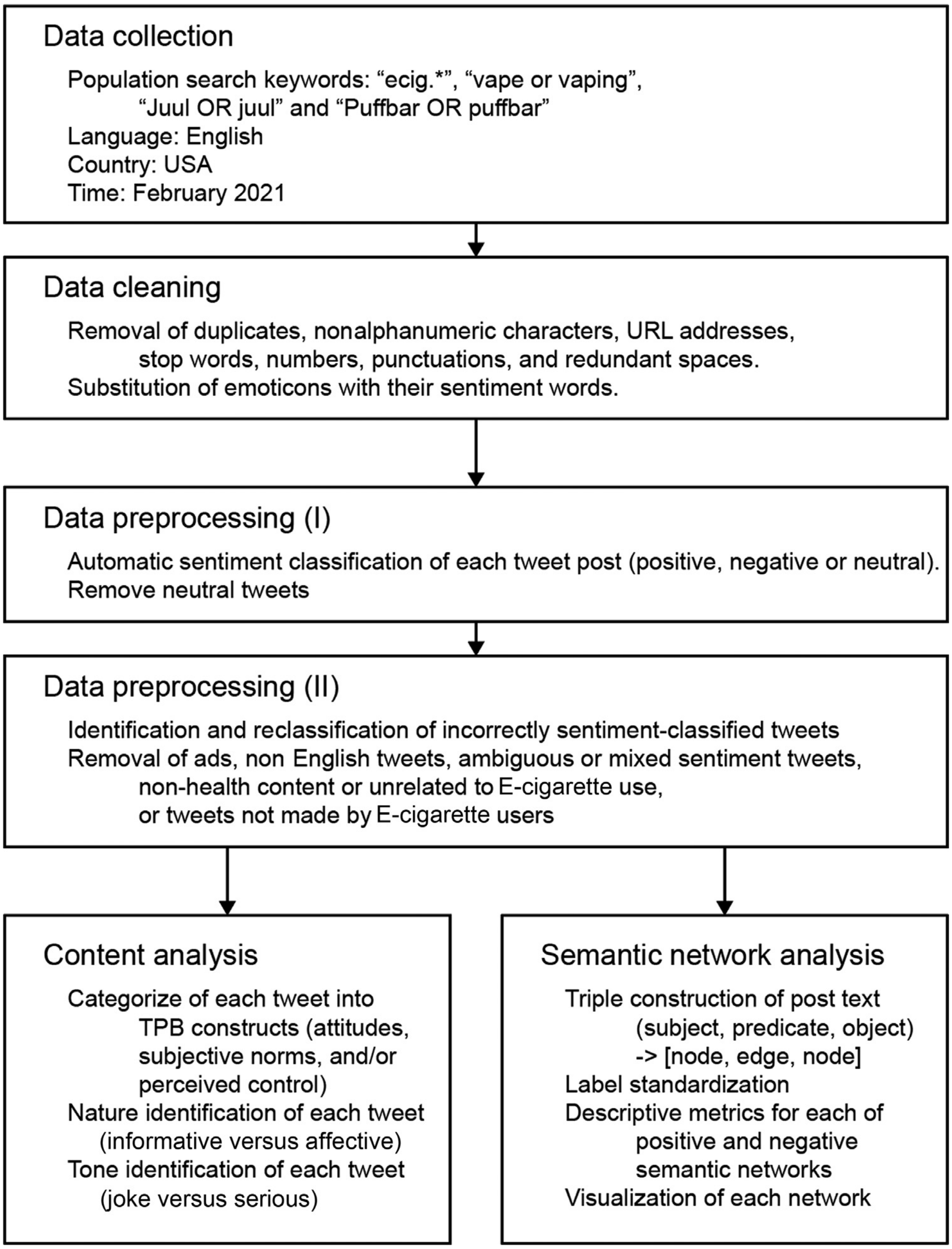

Figure 1. A diagram of study flow.
TPB, theory of planned behavior.

E-cigarette products in the U.S.—*Juul* or *juul* and *Puffbar* or *puffbar*—as population search keywords to identify potential E-cigarette users on Twitter. Our primary interest was among E-cigarette users who talk about E-cigarettes and vaping-related health beliefs through Twitter because talking about tobacco-related content on Twitter is associated with product use.[43] Duplicated tweets and retweets were removed. All emoticons were substituted with their sentiment word, and nonalphanumeric characters (i.e., @username), URL addresses, stop words, numbers, punctuations, and redundant spaces were removed. For this sample of tweets, automatic sentiment scoring was first performed in R 4.0.3, using syuzhet in CRAN package, which is based on NRC Lexicon.[44] Syuzhet algorithm compares words in the text data with NRC Sentiment and emoticon Lexicon, associating words with sentiment (positive, negative, or neutral). Neutral tweets were composed of mainly factual statements such as news headlines and neutral announcements, for instance, “You can now use your EBT cards at vape shops.” Because such statements cannot be simply assumed as E-cigarette users’ health beliefs or attitudes (even though they may contribute to beliefs and attitudes), neutral tweets were excluded from further analyses. On the basis of the number of positive and negative words, the sentiment of every non-neutral tweet was determined in a binary fashion (i.e., coded as positive or negative).

Measures

Next, we randomly ordered tweets by sentiment. Differences between sentiment were determined on the basis of consistency of statements that clearly identified sentiment group affiliation, such as encouraging E-cigarette use and highlighting benefits (positive sentiment) or discouraging E-cigarette use and highlighting risks (negative sentiment). Tweets were manually reviewed by 3 trained researchers to remove ads, tweets not written in English, incorrectly classified sentiments, ambiguous or mixed sentiment, and tweets that were nonhealth content or unrelated to E-cigarette use or that were not made by E-cigarette users, until we reached 1,000 unique tweets of E-cigarette users, stratified by sentiment (500 positive tweets and 500 negative tweets).

Coder training for this manual review process was conducted by the lead researcher using practice tweets collected outside of the analysis timeframe for this study and on Twitter accounts not included in the study. Upon completion of coder training, 3 independent coders were provided 10% (n=100) of the total tweets to determine intercoder reliability. Intercoder reliability was assessed using Krippendorff’s alpha, and coder training took place until an acceptable alpha level (>0.80) was reached. After the third round, an acceptable alpha level was achieved for ads (0.92), sentiment (0.98), health-related content (1.0), and E-cigarette user identification (1.0). Coders were then equally assigned the remaining tweets to determine the sentiment of each individual tweet—positive, negative, or neutral—and determined whether each tweet was an advertisement, was health-related content, and was made by an E-cigarette user. *Nonhealth-related content* was defined as a tweet that did not specifically reference health objectives or outcomes or factors that can contribute to shaping E-cigarette use behavior (e.g., Good morning, fellow vapers!). E-cigarette users were identified as individuals who reported current or past experiences of their own E-cigarette use in their posts.

Data Analysis

Content Analysis. Each tweet in the sample was categorized into TPB constructs: attitudes, subjective norms, and/or perceived control about E-cigarette use. The nature of each tweet was also identified: whether the main message was informative (a general topic, not related to an individual experience) or affective (a personal feeling/experience). Next, the tone of each tweet was classified according to whether it was a joke, according to the dictionary definition of a joke as “a thing that someone says to cause amusement or laughter, especially a story with a funny punch line.” All remaining tweets were considered serious tweets. The proportions of tweets for the 4 constructs were summarized using dplyr package in R.[45]

All coders were trained according to intercoder reliability procedures in previous studies.[46,47] Training included instructions, content categories, definitions, and an exercise analyzing posts from a pretest sample comparing results and discussing discrepancies until consensus was reached. One coder assessed all posts in the sample. Twenty percent were randomly selected and independently coded by 2 other coders. Overall intercoder reliability was found to be substantial to almost perfect for all variables, with average Fleiss’ Kappa coefficient of 0.80 and 90.7% agreement (Table 1).

Semantic Network Analysis. Semantic networks were assessed by sentiment group (positive or negative) and yielded undirected, unweighted graphs consisting of nodes that represent words and edges that correspond to extracted word relations.[48] Post-text was manually formatted as triples, in which subject, predicate, and object of each sentence correspond to node, edge, and node in the network, respectively. Node and edge labels were standardized to resolve lexical differences and grammatical dependencies. Resulting standards for network vocabulary were based on term frequency. For example, synonymous nodes labeled combustible cigarette, traditional cigarette, and regular cigarette were applied as the

Table 1. Fleiss’ Kappa and Percentage Agreement Measures Between All Coders

Measures	TPB construct	Nature	Tone
Positive			
Fleiss’ Kappa (k)	0.81	1.0	0.75
Percentage agreement (%)	96	100	83
Negative			
Fleiss’ Kappa (k)	0.75	0.87	0.64
Percentage agreement (%)	91	99	75

Note: Fleiss’ Kappa measures: almost perfect=1, 0.81; substantial agreement=0.80, 0.61; moderate agreement=0.60, 0.41; fair agreement=0.40, 0.21; slight agreement=0.20, 0; and poor<0.
TPB, theory of planned behavior.

Table 2. Topics in E-Cigarette Users' Positive-Sentiment Tweets About Vaping (N=500 Tweets)

Tweet category	*n* (% of tweets)	Illustrative examples (paraphrased to maintain the anonymity of the original posters)
Positive Sentiment (encouraging E-cigarette use and highlighting benefits)		
Health advantages of vaping (*n*=195, 39.0%)		
Help smoking cessation	192 (38.4) Serious=192 Joke=0 Informative=12 Affective=180	• Tobacco is shortening the life of every single user. Vaping will save many lives, so we must legalize it to make it widely available to tobacco users. I think vaping products are the only smoking cessation products that will enable me permanently quit smoking.
Improve physical and mental health	137 (27.4) Serious=115 Joke=22 Informative=13 Affective=124	• My vape oils contain vitamin E extract, which boosts my immune system. • I vape because the propylene glycol in e-cigarettes kills bacteria, this is why I don't get COVID. • I had been constantly anxious and I used to tend to hyperfocus on things until I discovered a vape pen that has worked great for all of these issues. I think it is true that we can use a vape for anxiety and ADHD. • I've lost 20lbs in a month since starting vaping. The physiological benefit of e-cigarettes is immeasurable.
Subjective norms (*n*=241; 48.2%)		
Generate positive social impact	183 (36.6) Serious=23 Joke=160 Informative=0 Affective=183	• I was able to pretend I was the absolute perfect babe holding my vape and make "bae" fall in love. • Love it when I pull out my vape and hit it and a whole bunch of hot girls start asking for my snapchat cause I'm apparently a "vape god." • I vape for the social aspect. Taking a vape break and socializing with other vapers. I met a lot of people this way.
Social support	131 (26.2) Serious=123 Joke=8 Informative=0 Affective=131	• Hearing about how people lose their relatives to smoking makes me glad most of my family and I that smoked have switched to e-cigarettes or vapes now. About to pressure my dad to get a vape instead of combustible cigarettes. • My parents aren't mad about my vape because my room smells like incense sticks and they actually like coming in to hug or talk to me. • At one point my teacher confronted me about vaping, but we had a conversation about it and I explained how the vaporizer worked and what was in the juice and a week later I saw the teacher vaping. I even recommended a couple of flavors and made a new friend.
Peer influence	49 (9.8) Serious=4 Joke=45 Informative=0 Affective=49	• My besties fueling my addictions and buying me vape juice and two empty pods for my birthday are the best gift. • A massive thanks to my friends for convincing me to make the switch to vaping.
Perceived behavioral control (*n*=151; 30.2%)		
Have control over addiction and intend to continue to vape	138 (27.6) Serious=120 Joke=18 Informative=15 Affective=123	• If you have had a bad vaping addiction, I advise you to take some over the counter chlorophyll. It will remove metals and toxins from your bloodstream and you'll be good. • I've only been vaping for a year but at this point in time I don't really have any plans to quit vaping. It helps me focus. • It's time to vape for now until I really don't feel I want cigs anymore. Then, I will start working on the nicotine. This is the only way to be successful at quitting smoking.
Have attachment to vape products	52 (10.4) Serious=13 Joke=39 Informative=0 Affective=52	• My vape in one hand and candy in the other and my phone in my pocket if that tells you my priorities. • I fall asleep my vape pen in my hand most nights. • Every night I fall asleep with my silly little vape in my hand and every morning I wake up and hit it.

ADHD, attention-deficit/hyperactivity disorder.

most commonly used term across same-sentiment documents (in this case combustible cigarette) to replace labels of all semantically equivalent nodes. For example, in a negative sentiment semantic network, the sentence "Vaping impacts my impulse control and magnifies my stress" was represented by 2 triples: (vape [node], impact [edge], impulse control [node]) and (vape [node], magnify [edge], stress [node]).

We applied several measures of network analysis to generate semantic networks to limit biased interpretation of selected network metrics. Descriptive statistics included network size, density, and diameter. Network size is the total number of topics (nodes), density measures the interconnectedness of topics, and diameter characterizes compactness of the network. We evaluated centrality (direct measures of which topics are likely to be activated repeatedly, even as different topics are mentioned). Modularity-based community detection algorithms described cohesive groups of topics in each network, and clusters of important topics were visualized. iGraph was used in network analyses and graph constructions in R.[49]

RESULTS

On the basis of search terms, we identified a total of 232,130 unique U.S. tweets made in February 2021. Most tweets (82.4%) included the *vape* search term. After removing retweets, 141,120 tweets remained. Half of the tweets (n=69,772) were in English. After neutral tweets (40.7%, n=28,386) were omitted, 54.4% of the remaining tweets were classified as positive vape sentiment (n=22,533), and 45.6% were classifiied as negative (n=18,853). We excluded 669 tweets that were ads, 152 tweets that were incorrectly sentiment classified, 151 tweets that were not made by E-cigarette users, and 799 tweets that were nonhealth related, resulting in a sample of 1,000 tweets for analysis. Tweets (n=1,000) were posted by 986 unique users (488 users in positive sentiment group and 498 users in negative sentiment group).

Content Analysis

Positive sentiment. As shown in Table 2, nearly half the positive sentiment tweets (n=241, 48.2%) contained information that could potentially shape E-cigarette users' normative beliefs toward E-cigarette use. In 195 tweets (39.0%), specific beliefs about positive likely outcomes of E-cigarette use behavior were mentioned. Beliefs on perceived behavioral control underlying E-cigarette use were indicated in 151 tweets (30.2%). Seven distinct topics related to E-cigarette use contexts emerged in positive sentiment tweets: (1) more than one third of tweets (n=192, 38.4%) indicated E-cigarette users' belief that vaping assists in smoking cessation, (2) 36.6% (n=183) of the tweets identified vaping as a cool product that can generate positive social impacts, (3) control over vape addiction with intention to continue to vape was in 138 tweets (27.6%), (4) 27.4% (n=137) of tweets indicated beliefs that vaping will improve their physical (e.g., smoking cessation or reduction aids, reduced risk of getting COVID-19, weight management, improved lung function and immune system) or mental health (e.g., depression and stress management, anxiety reliever, reduced attention-deficit/hyperactivity disorder symptoms), (5) 26.2% (n=131) noted that their family and friends are supportive of E-cigarette use, (6) about 10% of the tweets (n=52) indicated attachment to vape products, and (7) 49 tweets (9.8%) mentioned peer influence in E-cigarette use. Less than half the positive sentiment tweets were serious (n=209, 41.8%). The tweets classified as jokes were mostly found in the topics of peer influence (91.8%, 45 of 49), social impact (87.4%, 160 of 183), and attachment to vape product (75.0%, 39 of 52). No joking tweets were posted in the smoking cessation topic. Encouragement of willingness to continue vaping has been reported in E-cigarette users who are becoming attached to E-cigarette products and entangled with the E-cigarette in their lifestyle.[50] A handful of tweets (n=40, 8.0%) were informative; however, no references were provided in the message, only unsubstantiated assertations (e.g., "Propylene glycol in e-cigarettes kills bacteria. That's why people don't get COVID if they vape").

Negative sentiment. As shown in Table 3, around half the negative sentiment tweets (n=230, 46.0%) were about E-cigarette users' beliefs about the health disadvantages of vaping. Normative beliefs were found in 192 tweets (38.4%). A total of 155 tweets (31.0%) contained information on E-cigarette—perceived control beliefs. Nine distinct topics emerged: (1) 25.8% (n=129) of tweets contained self-reported negative physical health symptoms from E-cigarette use, (2) 22.2% (n=111) of the tweets indicated perceived addiction, (3) 22.0% (n=110) of the tweets concerned about the lack of regulations to prohibit E-cigarette use in enclosed public places, (4) 13.8% (n=69) of the tweets were related to effects of peer pressure in vaping initiation, (5) 13.2% (n=69) showed concerns about increased risk of COVID-19 (e.g., transmission of COVID-19 by sharing vapes and/or no social distancing), (6) 12.0% (n=60) reported negative effects on mental health, (7) 8.2% (n=41) reported nontherapeutic effects on smoking cessation, (8) 5.2% (n=26) reported conflicts with family and/or friends because of E-cigarette use, and (9) 4.4% (n=22) reported the potential impact of vaping on drug craving and polysubstance use. Most negative sentiment tweets were

Table 3. Topics in E-Cigarette Users' Negative Sentiment Tweets About Vaping (N=500 Tweets)

Tweet category	*n* (% of tweets)	Illustrative examples (paraphrased to maintain the anonymity of the original posters)
Negative Sentiment (discouraging E-cigarette use and highlighting risks)		
Health disadvantages of vaping (*n*=230; 46.0%)		
Negative physical health symptoms	129 (25.8) Serious=80 Joke=49 Informative=37 Affective=92	• Today, I read an article that bubble lungs were caused by vape carts and the pic was of a nicotine mod, so yeah, I didn't think about the safety of vaping until now but it seems risky. • My stomach hurts and I feel a "punched-in-the-chest" feeling. All I had this morning was vape dust. I feel like I'm waking the cancer up. • E-liquid contains calories and all the crappy chemicals in it messed with my metabolism and it made me gain weight.
Worry about COVID-19 infection	69 (13.2) Serious=29 Joke=40 Informative=15 Affective=54	• Sharing vapes with random people during a pandemic is reckless and immoral because you share spit with everyone, you are basically a super spreader. The only people I share my vapes with are my brother, my wife and my best friends. • I'm fine with sharing my vape at school but I bet the 99% of people getting COVID from vaping would drop if people stopped sharing their vapes. • They should prioritize me for the COVID vaccine because I vape.
Nontherapeutic effects on the severity of mental health	60 (12.0) Serious=13 Joke=47 Informative=2 Affective=58	• Experimented with vaping because the past few days was very stressful for me. Vaping didn't seem to relieve my stress. • Hitting the vape after washing down melatonin and zzzquil with valerian root tea at 3 AM. It doesn't really help me sleep, it only makes me tired and light-headed. • I used to vape and drink to cope with depression. It wasn't really a proper decision, but I didn't see any other way. Still can't stay calm. I continued to self-harm and I'm sad.
Have smoking relapse	41 (8.2) Serious=31 Joke=10 Informative=4 Affective=37	• I quit smoking 3 years ago with the help of a vape but I'm going back to the cigs until I pick up a proper vape again. • Bad news - vaping didn't work for me, I'm going back to smoking. I tried several of my favorite flavors and I'm still craving cigs. What's the point.
Subjective norms (*n*=192; 38.4%)		
Lack of regulations	110 (22.0) Serious=85 Joke=25 Informative=42 Affective=68	• Almost every day I see someone sneaking a vape in the middle of class, always when the professor isn't looking. Why do people think this is acceptable? I vape all the time, just not in class, or not in the bank. You are not allowed to vape in indoor areas. *https://www.cdc.gov/statesystem/factsheets/ecigarette/ECigarette.html* • My friends and I got addicted to vaping cause vape companies lie to us. Vape ads are out of control and we trust them more when they tell us something might be good for us.
Feel peer pressure	69 (13.8) Serious=51 Joke=18 Informative=0 Affective=69	• My friends constantly offered me a vape and I felt peer pressured into vaping with them. I tried once and my fear is getting addicted to nicotine and not being able to quit. Am I overreacting? • I finally gave into peer pressure, and I regret. I turned myself into someone who wasn't myself and as a result, I felt crappy.
Conflicts with family and/or friends	26 (5.2) Serious=9 Joke=17 Informative=0 Affective=26	• My wife hates smoking so I quit, then started vaping. She still considers this smoking so I'm hiding that and it makes me feel guilty. • Vaping isn't cool. I ditched my friend for "cooler" ones who vaped. I now realize they weren't my friends, but dictators of my life.
Perceived control (*n*=155; 31.0%)		
Become addicted to vaping	111 (22.2) Serious=65 Joke=46 Informative=29 Affective=82	• I have been addicted to nicotine by vaping for a while and it is not good for me. I hate it but can't stop. Need help. • I find vaping as addictive as cigs, it's not just a matter of nicotine. I used to vape all day the first year I started because I liked doing cloud-chasing, now I like its throat hit. It's hard to stop doing

(*continued on next page*)

Table 3. Topics in E-Cigarette Users' Negative Sentiment Tweets About Vaping (N=500 Tweets) (*continued*)

Tweet category	*n* (% of tweets)	Illustrative examples (paraphrased to maintain the anonymity of the original posters)
		something when you like it, even if you know it's bad for your health. • I have linked many things to vaping, like vaping while taking a dump, vaping after a meal, vaping while driving. . . Quitting those behavioral patterns is more challenging than just doing it cold turkey.
Polysubstance use	22 (4.4) Serious=4 Joke=18 Informative=0 Affective=22	• Not really anything is too strong for me anymore. I have tried CBD vapes to see if it would work to help me sleep but they didn't. My brain won't shut up unless I mix them with DMT edibles. • I've heard some success stories about salvia, read amphetamines can be vaped, been getting curious about vaping other psychedelics.

CBD, Cannabidiol; DMT, N, N-Dimethyltryptamine.

classified as serious (*n*=367, 73.4%). Common topics among serious tweets were lack of regulations (77.3%, 85 of 100), peer pressure (73.9%, 51 of 69), noneffectiveness in smoking cessation (75.6%, 31 of 41), and negative physical health symptoms (62.0%, 80 of 129). About a quarter of the tweets (*n*=129, 25.8%) were classified as informative, with greatest proportions found in the lack of regulations (38.2%, 42 of 110) and physical health symptoms (33.6%, 37 of 129). Twenty-four informative tweets (18.6%) provided references to support the information they share (e.g., "Almost every day I see someone sneaking a vape in the middle of class. https://www.cdc.gov/statesystem/factsheets/ecigarette/ECigarette.html").

Semantic Network Analysis

Network properties of tweet texts are summarized in Table 4. Negative sentiment tweet texts formed a larger semantic network, with a network size (number of nodes) of 4,859, than the smaller network of positive sentiment tweet texts, with a network size of 1,971. Network size indicates the number of topics in the network, whereas density describes interconnectedness of the topics. The largest cluster of nodes in the negative sentiment network was larger in size than in the positive sentiment network (133 nodes[topics] vs 100 nodes, respectively), but it was less dense than the positive network (densities=0.042 vs 0.071).

Community detection analysis identified 16 distinct communities within the positive network and 21 communities in the negative network, providing a more detailed view of topics identified from the manual content analysis. Communities and density measures for the positive network suggest a more cohesive and interconnected belief system among positive sentiment topics than for the larger, less-connected network of negative sentiment. The average clustering coefficient (i.e., the tendency of topics to form a group) and average node centrality were higher for the positive network than for the negative. The negative network exhibited a greater diameter and longer average path length (8 and 4.385, respectively) than positive network (6 and 3.569, respectively). Excluding expected nodes such as vaping, the most central topics for the positive sentiment network included smoking cessation aid, COVID-19, lung cancer, mental health, sleep, youth, study, party, drink, fashionable, destress, and flavor. Significant topics within the negative sentiment network were nicotine withdrawal, vape addiction, headache, chest pain, cough, chronic obstructive pulmonary disease, marijuana, drug, alcohol, depression, anxiety, friend, pressure, smoking relapse, indoor use, and regulation. The most central topics were ranked in size by degree centrality and plotted in Figure 2.

Table 4. Summary of Measures for Sentiment-Specific Tweet Text Networks and the Corresponding Greatest Connected Component

Measures	Positive sentiment	Negative sentiment
All selected tweets		
Number of nodes	1,971	4,859
Number of edges	4,131	10,908
Average degree	4.837	2.192
Modularity	0.461	0.368
Clustering coefficient	0.131	0.096
Greatest component subgraph		
Number of nodes	100	133
Number of edges	302	339
Graph density	0.071	0.042
Network diameter	6	8
Average path length	3.569	4.385
Average degree	6.140	5.709
Average degree centrality	0.016	0.010
Number of communities	16	21
Average clustering coefficient	0.288	0.240

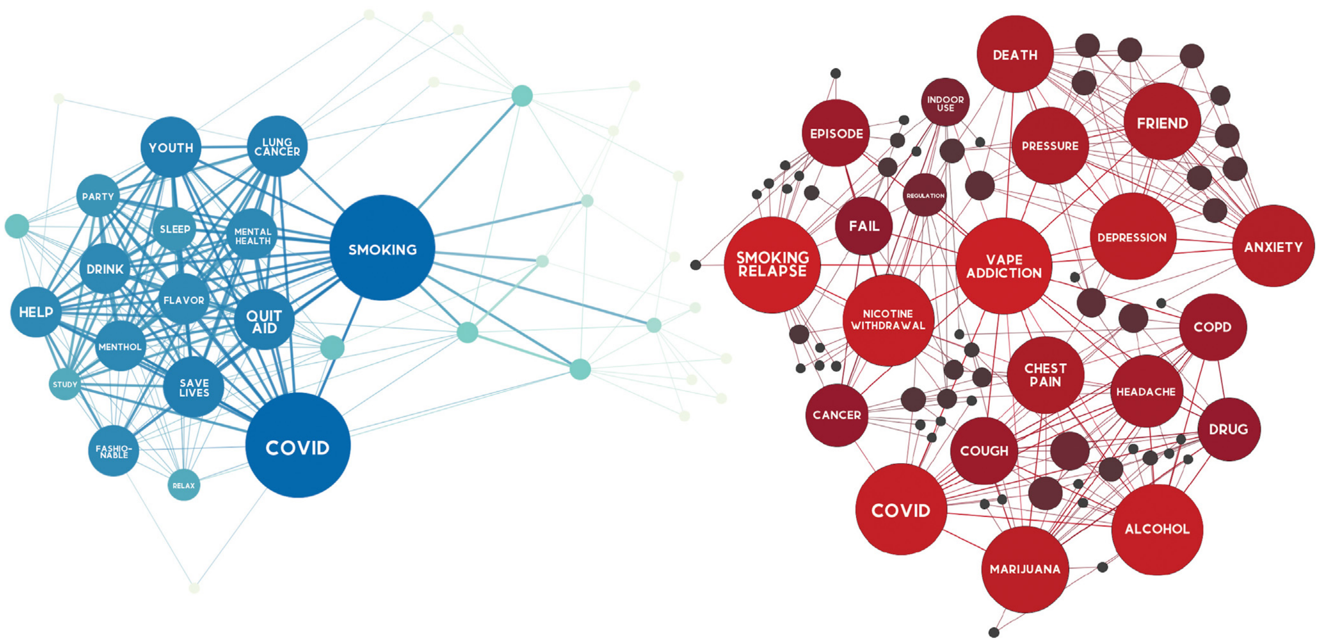

Figure 2. Positive (blue, on the left) and negative (red, on the right) E-cigarette use health belief semantic networks.

DISCUSSION

We identified the most salient conversation topics corresponding to each theoretical construct of TPB by analyzing a random sample of 1,000 E-cigarette users' tweets from the U.S. collected over a month period at the national level. Through semantic network analysis, we further investigated how a broad range of topics are interconnected in the social media discourse. The study revealed health beliefs in positive and negative messages within E-cigarette use related Twitter posts. This included differences in term valence such as expectation versus reality, social impact versus social conflict, peer influence versus peer pressure, attachment versus addiction, and social commentary versus evidence-based science related to issues of support and regulation of E-cigarette use.

Tweets encouraging E-cigarette use were characterized by dense semantic networks with fewer topics and stronger connections. These results indicate that online information about positive aspects of E-cigarette use is concentrated on a few significant topics. On the contrary, tweets discouraging E-cigarette use presented a greater number of topics with relatively low connectivity. In addition to the central negative topics such as smoking relapse and nicotine addiction, the broad distribution of topics of perceived negative side effects and worsened health consequences contributed to E-cigarette users' attitudes toward vaping. This finding highlights the impact of repeated exposure to favorable messages about E-cigarette use on the basis of previous studies that suggest that the frequency of messaging is related to behavioral intention.[51,52] On the basis of our findings, negative tweet topics were broad and not deep; therefore, individuals seeking information on vaping were more likely to be exposed to the same topic in positive tweets and are likely to perceive the frequency of messaging because evidence is toward vaping. A few vaping prevention programs have reflected the assumption that education about a range of negative effects of vaping will help to resist the vaping behavior.[53] Our analysis results suggest that risk education alone might not have enough influence on vaping intention. Vaping prevention programs could be more effective if more emphasis is on correcting the idea of vaping as a smoking cessation aid with streamlined messaging and topics.

A common misconception is that E-cigarettes can aid in smoking cessation and have a curative value on health symptoms. Although we did not classify tweets for misinformation, many tweets contained incorrect information about ingredients. For example, propylene glycol in E-cigarette liquids was believed to reduce the risk for COVID-19. However, propylene glycol is known for its toxic effects on the lungs.[54,55] Vaping was also identified as relieving anxiety and depression, although the therapeutic effects of vaping on mental illness have not been shown. Public health efforts should prioritize the prevention and containment of misinformation about E-cigarette ingredients and medical benefits, given that Twitter and other online social media platforms can be used to disseminate health information.[56−58] Education about E-cigarettes, including harm from toxic ingredients, the lack of evidence on its role as a cessation tool,[59−64] and creating social awareness regarding misinformation, should be addressed.

Roughly 40% of positive tweets indicated the possession of E-cigarettes to generate social impact (e.g., becoming more popular) and as a source of self-presentation (e.g., looking fashionable and attractive). Many E-cigarette users who self-identified as young adults or adolescents expressed their desire to seek new impressions in social events. Encouragement from personal network to use E-cigarettes was also motivation for many people to initiate vaping—jokes in these tweets were frequently related to enjoyable experiences in peer group settings. Young E-cigarette users also reported peer pressure as the most important reason for vaping initiation. A quarter of negative tweets expressed concerns about the impacts of lack of E-cigarette regulation, including the impact of lowering risk perception that could lead to greater perceived social approval of E-cigarette use behavior. These findings suggest that smoking cessation may not be the main motivator for vaping initiation among young people. Although the temporal precedence and causality cannot be fully shown in this study, strong social motives of vaping in young people for social acceptance may lead to vaping that could put them at risk for combustible cigarette use and other harmful products.

Although many people perceive E-cigarettes as less harmful than combustible cigarettes, they may not be safe considering the limited regulation around manufacturing[65,66]; potentially dangerous ingredients and incorrect nicotine levels have been identified.[67,68] In addition, E-cigarettes can deliver high dosages of nicotine, comparable with or higher than levels observed among regular smokers,[69] which can lead to nicotine addiction. About a quarter of negative tweets reported the effect of biological craving for vaping combined with daily use of nicotine. A range of signs of vaping addiction were described, including various experiences related to loss of self-control and regulation for vape use and regrets of initiating vaping. Although many users were confident that they could use without becoming dependent, nicotine withdrawal appeared to maintain their use. Previous studies have reported that E-cigarette users' perceptions of addiction are lower than those of combustible cigarette users.[70,71] Taken together, these findings suggest that interventions to prevent or reduce vaping should include information about the strong potential for addiction and integrate treatments for nicotine dependence in the clinical settings.

A considerable proportion of the negative sentiment tweets expressed disappointment regarding the absence of therapeutic effects for their mental health (e.g., anxiety and depression) and experiences of adverse physical effects (e.g., chest pain, shortness of breath, sore throat). Some users believed that vaping increased anxiety and depression and has led to polysubstance use to create a synergistic stimulant effect between nicotine and antidepressant medications. Although it is unclear whether experiencing adverse physical and mental health symptoms is directly related to E-cigarette use, it is possible that vaping to self-medicate for mental health problems could lead to excessive use and using multiple substances. Previous studies have reported positive associations between depression, anxiety, and nonmedical drug use.[72−74] Potential strategies to reduce use could include addressing self-medication and teaching appropriate mental health care.

Limitations

One social media platform was used for analysis. Although Twitter is a popular platform for these issues, there are other platforms where similar discussions occur (e.g., Facebook, Instagram, TikTok). Because our sample contained English-only tweets, the data may not fully represent society and could be biased toward certain sociodemographic characteristics such as younger audiences. Furthermore, the tweets were limited to those written in the U.S.; the findings may not reflect the characteristics and attitudes of global E-cigarette users. Future studies should include additional social media platforms and languages to provide a deeper understanding of issues surrounding vaping epidemics.

CONCLUSIONS

This study adds to the tobacco control research using mixed methods to identify and discuss, on the basis of TPB, the most salient behavioral, normative, and control beliefs of E-cigarette users about vaping. Recognition of these beliefs may develop a better understanding of the origins of the attitudes, the subjective norms, and the perceived controls to the vaping. The practical implications of this study may inform psychological and behavioral interventions in various settings. Specifically, interventions could benefit by increasing knowledge and reducing favorable attitude regarding the E-cigarette use. In addition, because our results indicated that there were strong help-seeking intentions, researchers and clinicians may want to help E-cigarette users with mental illnesses develop some coping skills to overcome commonly faced stressors. Adolescents and young adults, especially students, appeared the most vulnerable group and are at increased risk of E-cigarette use because of social motives compared with other populations.

Research to examine students' knowledge and perceptions toward E-cigarette use would be vital to inform intervention strategies to prevent and control E-cigarette use among young people.

ACKNOWLEDGMENTS

This research was supported by the USC Tobacco Center of Regulatory Science (Grant number 5U54CA180905-09; prinicpal investigator: JBU)

Declarations of interest: none.

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