



Relationship between social media engagement and e-cigarette policy support



Anuja Majmundar*, Chih-Ping Chou, Tess B. Cruz, Jennifer B. Unger

Department of Preventive Medicine, University of Southern California, 2001 North Soto Street, 3rd Floor, Los Angeles, CA 90032, United States

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ABSTRACT

Introduction: Given increasing efforts to regulate e-cigarettes, it is important to understand factors associated with support for tobacco regulatory policies. We investigate such factors found in social media and hypothesize that greater online engagement with tobacco content would be associated with less support for e-cigarette regulatory policies.

Methods: We constructed social networks of Twitter users who tweet about tobacco and categorized them using a combination of social network and Twitter metrics. Twitter users were identified as representing leaders, followers or general users in online discussions of tobacco products, and invited to complete an online survey. Participants responded to questions about their engagement with tobacco-related content online, degree of support for e-cigarette regulations, exposure to tobacco marketing, e-cigarette use and other demographic information. We examined links between their reported engagement with tobacco-related content and support for e-cigarette regulatory policies using structural equation modelling.

Results: The analytic sample consisted of 470 participants. The conceptualized structural equation model had a good fit ($\chi^2(32) = 24.85, p = 0.09, CFI = 0.99, RMSEA = 0.03$). Findings support our hypothesis: engagement with online tobacco content was negatively associated with support for e-cigarette policies, while controlling for e-cigarette use, tobacco marketing exposure, social media use frequency and demographic factors.

Conclusions: Findings suggest that our hypothesis was supported. Twitter users engaging with tobacco-related content and harboring negative attitudes toward e-cigarette regulatory policies could be an important audience segment to reach with tailored e-cigarette policy education messages.

1. Background

Tobacco regulatory policies reduce smoking rates by restricting tobacco use, increasing barriers to smoking (e.g., taxes), denormalizing smoking among youth, and limiting public exposure to tobacco marketing (Hopkins et al., 2010; Shelton et al., 1995; Unger et al., 1999). For tobacco regulatory policies to be effective, public support is crucial to ensure that supporters vote for these policies, enforce them and comply with them. While there is substantial research examining characteristics of individuals with high or low support for tobacco regulatory policies, factors driving support for tobacco regulatory policies are not well-understood (Dai, 2017; Goldstein et al., 1997; Kowitz, Goldstein, Schmidt, Hall, & Brewer, 2017; Unger et al., 1999; Unger, Barker, Baezconde-Garbanati, Soto, & Sussman, 2016; Unger, Barker, Sussman, Soto, & Baezconde-Garbanati, 2016; Wackowski & Delnevo, 2015).

Policy support factors may derive from public discourse about e-

cigarette policies, which is situated in a larger debate about whether e-cigarettes lead to nicotine addiction or help people quit combustible cigarettes (Malone, 2016). The fact that e-cigarettes are sold online, and offered in a variety of flavors, some with no nicotine content, further complicates the issue of regulating all e-cigarette products (Lazard, Wilcox, Tuttle, Glowacki, & Pikowski, 2017).

Social media platforms such as Twitter, Instagram and Facebook are viewed as online services that allow communities to collaborate, connect, and interact with user-generated or shared content that is modified, shared and engaged with over time (McCay-Peet & Quan-Haase, 2016). In the context of tobacco products such as e-cigarettes, these platforms offer opportunities for the public to engage with tobacco-related content and in e-cigarette policy discussions (Hamill, Turk, Murukutla, Ghamrawy, & Mullin, 2015; Harris et al., 2014; Ross, Dearing, & Rollins, 2015). Engagement, in this context, is defined in terms of experiences that are either driven by personal habits or preferences (e.g., coming across a Youtube video and watching it) or

* Corresponding author.

E-mail address: anuja.majmundar@usc.edu (A. Majmundar).

involving discussions and socializing with others on the internet (e.g., involves posting, liking/sharing posts) (Calder, Malthouse, & Schaedel, 2009). Social media engagement with tobacco-related messages or campaigns makes these topics salient among audiences, facilitates targeted and rapid dissemination of marketing messages, and provides an indicator of viewer involvement for real-time monitoring of public engagement (Allem et al., 2017; Jawad, Abass, Hariri, & Akl, 2015; Vallone et al., 2017). Research suggests that pro-tobacco content exceeds anti-tobacco content on social media, part of which consists of messages against tobacco regulations, particularly on Twitter (Allem, Escobedo, et al., 2017; Ashley & Tuten, 2015; Zhan, Liu, Li, Leischow, & Zeng, 2017). As such, interaction with predominantly anti-tobacco content encompassing anti-tobacco policy perspectives, may reflect in peoples' attitudes.

Social media users potentially engage with tobacco-related content from multiple sources. One of them relates to content posted by other social media users, interested in exchanging ideas about tobacco regulatory policies. These users may support or actively counter policy efforts. For instance, in 2014, the Chicago Department of Public Health's e-cigarette campaign was "Twitter bombed" by opponents of a proposed local e-cigarette regulation who used an account or whose tweets included elements in line with "astroturfing"—a strategy to convey a false sense of consensus around an idea (Harris et al., 2014). Analyses of user tweets in response to this campaign revealed that most of the negative comments came from Twitter users outside of the Chicago area. In fact, Chicago residents were more likely to be in support of the proposed regulation.

When social media users demonstrate engagement with posts, they might also be responding to content posted by automated social media agents or bots. Research suggests that bots are increasingly commonplace and can favor a one-sided view of tobacco products such as emphasizing use of electronic cigarettes for cessation (Allem, Ferrara, Uppu, Cruz, & Unger, 2017). Social media users find these bots to be as credible, attractive, competent, and interactional as human users; therefore, exposure to multiple messages from bots operated by tobacco brands or anti-e-cigarette policy groups could skew social media users' perceptions of tobacco and tobacco policy-related social norms (Edwards, Edwards, Spence, & Shelton, 2014; Melville, 2013).

Additionally, social media users may interact with posts from tobacco companies or pro-e-cigarette advocacy groups that are known to mobilize opposition to e-cigarette regulation (e.g., Cox, Barry, & Glantz, 2016; Harris et al., 2014). Engagement with and exposure to tobacco marketing content, in particular, is largely unregulated by the FDA and is a likely risk factor for onset of tobacco use, increased frequency of use and poly-product use (Pokhrel et al., 2018; Soneji et al., 2018; Unger et al., 2018). Literature suggests that these tobacco marketing messages are diffused beyond core supporters of e-cigarettes to the general public who are not necessarily seeking out information about e-cigarettes (Chu, Sidhu, & Valente, 2015). Part of this content includes messages that oppose tobacco control policies and promote smoking choices as acts of freedom (Chu et al., 2015; Dorfman, Cheyne, Friedman, Wadud, & Gottlieb, 2012). Exposure to such tobacco messages may decrease support for e-cigarette policies.

Social media engagement with tobacco-related content authored by social media users, bots and/or tobacco companies play an important role in steering public support for or against e-cigarette regulations. Using self-report data from Twitter users, we hypothesized that user reported engagement with online tobacco content predicts lower support for e-cigarette policy regulations, after controlling for key covariates and other demographic covariates.

2. Methods

Twitter data were obtained using a custom program that accessed Twitter's Streaming API to collect tweets containing at least one of over 200 tobacco-related keywords (e.g., "e-cigarettes", "vaping"). The data

included the text of the tweet, username of the person who posted the tweet and whether the tweet was an original tweet or a retweet.

This information was used to construct the social network of Twitter users where connections represent retweets of messages from one user to the other using the network analysis software, Gephi 0.9.1. First, a network was generated by linking users who had retweeted another user. Second, clusters of Twitter users were identified using modularity analysis. Modularity analysis identifies clusters within a network by grouping nodes or Twitter users, who have more connections (i.e., retweets) with others within a group than those outside of the group (Newman, 2006). Third, from each cluster, *Opinion leaders* were chosen as those who had been retweeted the most; *Followers* were identified within each cluster as those who had retweeted others the most. *General users* were outside the networks, and independently found by Twitter's API get-user-status function, which returns users who have recently posted a tweet. The opinion leaders had a median of 1000 followers, whereas followers and general users had fewer than 600. This method produced a convenience sample of opinion leaders, followers, and general Twitter users who occupy different positions within the tobacco social network. This sampling design ensured that the sample was not overrepresented with Twitter users who retweet the most. Twitter was selected as an example of a social media platform because its data are readily available, and Twitter is one of the most popular social media platforms (Pew Research Center, 2018).

From January–December 2016, Twitter users identified in the above networks were sent private messages inviting them to participate in a survey on their social media behaviors/preferences and support for e-cigarette regulations among other survey items. Each private message contained a unique, randomly-generated link to a RedCap site where the survey was hosted. When a participant clicked on the link, it identified the person as an opinion leader, follower, or general user who had been invited to complete the survey. Only those who received an invitation link could complete the survey. On clicking the link, the participants saw an IRB-approved consent script. After consenting to participate, each participant was directed to the online survey. The sample consisted of 877 participants (opinion leaders (N = 344), followers (N = 341), and general Twitter users (N = 192)) who completed surveys about their health behaviors, social media use, and views about their tobacco products by the end of December 2016. All participants were over 18 years, able to complete an online survey in English, and received a \$20 gift card for completing the survey. All procedures were approved by the authors' Institutional Review Board.

3. Measures

3.1. Support for e-cigarette regulatory policies

Four questions assessed support for e-cigarette regulatory policies (1- strongly favor, 5 - Strongly oppose; reverse coded). Questions covered topics such as support for a state law prohibiting e-cigarette use, taxing these products, regulating and licensing shops selling these products, and restricting flavorings. These policies were selected because they were being considered by several US states at the time of the survey (2016). These questions were indicators of the outcome latent factor - support for e-cigarette policies (Cronbach's $\alpha = 0.81$).

3.2. Online engagement with tobacco content

Drawing from previous research (e.g., Soneji et al., 2017), participants were asked to indicate "yes" or "no" to seven questions. Those who responded with "yes" to any one of the seven questions, were considered as engaging with online tobacco content. Questions pertained to seeing a video about tobacco or nicotine products on Youtube, posting about tobacco or nicotine products on Facebook/Instagram/ Youtube, visiting an e-cigarette, vape pen, mod or other electronic vaping device website in the past one month; using a smart phone or

tablet to scan a QR code that is unique for each tobacco product, participating in a sweepstakes or drawing from a tobacco company-sponsored contest, signing up for email alerts about tobacco products, or reading an article online about tobacco products.

3.3. Covariates

3.3.1. Exposure to tobacco marketing

A five-point scale (1-Never, 5- Very often) captured responses to the following question: “Thinking about everything that happened around you in the past 6 months, how often have you noticed things that promote tobacco or other nicotine products?”

3.3.2. E-cigarette use

All respondents who answered the question about whether they had used e-cigarettes in the past month were included. Response categories comprised of 1 = “yes” and 2 = “no”.

3.3.3. Demographic covariates

Age (median split, < / = 21 yrs., > 21 yrs.), race (White vs. Non-White, prefer not to answer), ethnicity (Hispanic/Latino vs. Not Hispanic/Latino, unknown/not reported), income (\leq \$49,000, > \$49,000 per year, prefer not to answer), education level (< / = high school, > high school, prefer not to answer), sex (male, female), and social media exposure (number of times/day a participant visits social media sites; 1 - several times, to 4 - monthly or less). Covariates with non-normal distributions such as age and level of education were transformed into dichotomized variables based on median splits. Skewed distributions were the primary reason for dichotomized splits for these variables. Those indicating “prefer not to answer” were marked as missing after sensitivity analyses for advertising exposure, race, ethnicity, education level, income, frequency of social media use covariates (see Results section).

4. Analysis

Univariate descriptive statistics were calculated for all variables of interest using SAS 9.4. Then EQS 6.3 was used for confirmatory factor analysis and structural equation modelling. Although our hypothesis can be examined using regression analysis, SEM reduces bias in measurement errors by controlling them statistically and allows for simultaneous testing of all variables in the model in order to assess model fit (Byrne, 1994; Peyrot, 1996).

4.1. Structural equation modelling (SEM)

4.1.1. The measurement model

The relationship of the indicators to their respective latent factor (outcome) was empirically assessed through confirmatory factor analyses using the EQS 6.3 computer software program (Bentler, 2004). Factor loadings of indicator variables were expected to have high loadings > 0.5 on the latent factor.

4.1.2. The structural model

Following inspection of confirmatory factor analysis results to verify the presence of a distinct construct of support for e-cigarette policies, causal pathways were included in the model to clarify the relationship between support for e-cigarette regulatory policy and online engagement with tobacco content. Covariates and the predictor were allowed to covary with each other. The hypothesized structural model was then tested.

4.1.3. Model fit

Model fit was assessed using the goodness-of-fit χ^2 test statistic, the comparative fit index (CFI) and the root mean squared error of approximation (RMSEA). CFI > 0.9 and RMSEA of < 0.05 was considered

a good fit (Bentler & Cudek, 1993; Kline, 1998). Distributions of all variables were checked for normality by referring to kurtosis and skewness statistics. The maximum-likelihood procedure was employed as a global test (Breckler, 1990).

The final model excluded non-significant covariates for model parsimony. This model consisted of the predictor variable of interest – online engagement with tobacco content, key covariates – exposure to tobacco marketing and e-cigarette use in the past 30 days, and two significant covariates – male, age.

5. Results

Participants (N = 877) were 54.0% female, 49.3% aged 21 years or younger, with 63.4% having at least a high school education, 77% earning less than or equal to \$49,999 per year, 65.6% White, 23% Hispanic/Latino. The sample size for those with complete data was 587 participants and those with incomplete data was 290 participants. There were significant differences between those with complete data (N = 587) vs. those with incomplete data (N = 290) across all variables (i.e. all variables had some missing data). Those with complete data reported lower social media use (p = 0.01) and income (p = 0.01). Next, sensitivity analysis indicated that the results did not change when those who marked “prefer not to answer” or “unknown/not reported” (N = 118) were excluded from analyses. The resulting sample size was 470 participants who had complete data for all variables in the analysis. Table 1 presents sample statistics for the non-imputed sample with

Table 1
Sample characteristics (N = 470).

Participant characteristics	N	%
Engagement with tobacco content		
No	248	52.77
Yes	222	47.23
Exposure to tobacco marketing		
Never	26	5.53
Rarely	159	33.83
Sometimes	175	37.23
Often	71	15.11
Very often	39	8.30
E-cigarette use in the past 30 days		
No	366	77.87
Yes	104	22.13
Age		
> / = 21 years	208	44.26
< 21 years	262	55.74
Sex		
Female	248	52.77
Male	222	47.23
Race		
White	318	67.96
Non-white	152	32.34
Ethnicity		
Hispanic	108	23.19
Non-Hispanic	361	76.81
Education level		
Complete high school or under	357	75.96
Beyond high school	113	24.04
Annual income		
< / = \$49,000	296	62.98
> 49,000	174	37.02
Social media exposure		
1- Several times	363	77.23
2-	96	20.43
3-	9	1.91
4-Monthly or less	2	0.43

E-cigarette use in the past 30 days, age (median split, < / = 21 yrs., > 21 yrs.), race (White vs. Non-White), ethnicity (Hispanic/Latino vs. Not Hispanic/Latino), income (< / = \$49,000, > 49,000), education level (< / = high school, > high school), sex (male, female), and Social media exposure (1 - several times to 4 - monthly or less).

Table 2
Factor loadings, response ranges, means, and deviations (SD) of the outcome variable – support for e-cigarette policy (1 – strongly oppose, 5 – strongly favor).

Factor and measured variables (1 = strongly oppose, 5 = strongly favor)	Mean	SD	Factor loading
My state should tax e-cigarettes and other vaping products, and devote the money for public education programs, research and the enforcement of laws relating to their use.	3.57	1.47	0.85
My state should regulate and license shops that sell e-cigarettes and other vaping products in the same way as stores that sell regular tobacco cigarettes.	3.759	1.38	0.83
My state should pass a state law that restricts adding flavors to e-cigarettes and other vaping products to reduce their appeal to young people.	2.71	1.55	0.72
My state should pass a state law prohibiting the use of e-cigarettes and other vaping products in places where smoking is not allowed, such as in restaurants, bars and workplaces.	3.44	1.48	0.84

Table 3
Summary results of model development (N = 470).

Model #	χ^2	df	p	CFI	RMSEA
1 With significant and non-significant covariates	45.24	32	0.06	0.987	0.030
2 With significant covariates and key non-significant covariates	24.85	17	0.097	0.99	0.031

complete data.

5.1. Factor analysis

The measurement model was tested using confirmatory factor analyses of support for tobacco policies. Results show that all variables loaded highly on four respective factors and the factor loadings were significant. This serves as evidence of construct and convergent validity. Robust estimates were computed. Results of the factor analysis are presented in Table 2.

5.2. Structural equation modelling

Model 1 included all the nine covariates and the predictor variable - engagement with online tobacco content. Supplemental Table 1 presents the covariance matrix used for SEM analysis. SEM analysis revealed that Model 1 offered an excellent fit ($\chi^2 (32) = 45.24, p = 0.06, CFI = 0.99, RMSEA = 0.03$). It was found that many of the covariates

except sex (males), age, and e-cigarette use were non-significant in Model 1. As part of sensitivity analyses, we imputed missing values using the expectation-maximization imputation algorithm. Resulting model from the imputed sample yielded a similar fit ($\chi^2 (32) = 72.19, p = 0.01, CFI = 0.98, RMSEA = 0.04, N = 877$), and significant covariates. The significant p-value associated with the chi-square test was expected because large sample sizes inflate the chi-square statistic. Based on the results of the sensitivity analyses, we report estimates from the non-imputed sample with complete data from hereon.

In Model 2, we excluded all non-significant covariates except one non-significant key covariate in the model – exposure to tobacco marketing, which was considered to be theoretically important. It consisted of one significant predictor, one non-significant covariate (exposure to tobacco marketing), and three other significant covariates (age, sex (males), and e-cigarette use). Model 2 revealed a good fit with data ($\chi^2 (17) = 24.85, p = 0.097, CFI = 0.99, RMSEA = 0.03$). Results of the development of the model are summarized in Table 3. Detailed standardized parameter estimates of the final model are presented in Fig. 1. Higher engagement with online tobacco content was associated with lower support for e-cigarette policies. Exposure to tobacco marketing had a non-significant relationship with support for e-cigarette policies. Other covariates – e-cigarette use and female had a significant and negative relationship whereas age had a significant and positive relationship with the outcome. The model accounted for significant relationships between engagement and the key covariates – exposure to tobacco marketing and e-cigarette use.

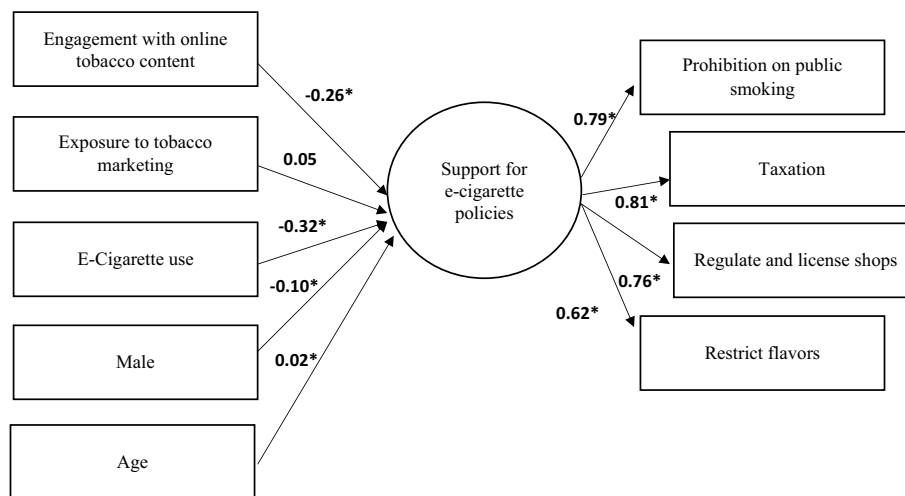


Fig. 1. Structural model for relationship between online engagement with tobacco content and support for e-cigarette regulatory policies (higher values indicate high support).

Note: Estimates are standardized co-efficients; *p < 0.05. $\chi^2 = 24.86, df = 17, p = 0.097, CFI = 0.99, RMSEA = 0.03$.

6. Discussion

This study examined associations between engagement with online tobacco content and support for e-cigarette regulatory policies. As hypothesized, our model shows that social media users who engage with posts about tobacco tend to have lower support for e-cigarette policies.

The findings contribute to an emerging body of evidence on implications of social media engagement on support for e-cigarette policies. Previous studies have described public support for tobacco regulations (Lazard et al., 2017; Nayak, Kemp, & Redmon, 2016; Wackowski & Delnevo, 2015). Recent work has also examined effects of social media user engagement with tobacco-related content on tobacco use initiation both longitudinally and cross-sectionally (Soneji et al., 2017, 2018; Unger et al., 2018). Our research makes critical connections between social media user engagement and support for tobacco regulations based on a diverse sample of Twitter users. This research is timely because exposure to online pro-tobacco content has increased over time (Duke et al., 2009; Richardson, Ganz, & Vallone, 2015), and the emergence of social media makes it possible for users to interact with and be influenced by such content (Soneji et al., 2018).

Several reasons may explain this association between engagement with tobacco-related content and support for e-cigarette policies. First, those who engage with tobacco content may identify with peers who do the same. This identification of like-minded peers could lead to tightly knit clusters where individuals locate themselves in a circle and keep endorsing and sharing content with a similar sentiment, like an echo chamber (see Hershey, 2009; Lorien, Joseph, & Dana, 2015). Studies show that an individual is likely to be a retweeter when the content of a tweet (retweeted by an individual at a later point) matches his/her earlier tweets (Lee, Mahmud, Chen, Zhou, & Nichols, 2014; Luo, Osborne, Tang, & Wang, 2013). We also know that anger tends to travel faster than joy via retweets and spreads easily to other user networks/strangers, which raises important implications for our findings (Coviello et al., 2014; Fan, Zhao, Chen, & Xu, 2014). Anti-e-cigarette sentiment can spread rapidly and widely to create misperceptions about group consensus and a false reflection of the reality (Bakshy, Messing, & Adamic, 2015). Additional research is needed to clarify the role of density of peer-clusters and dominant regulation-sentiments in driving support for e-cigarette regulation.

Second, the advent of social media analytics also targets users with attitude-consistent information. While some social networking sites such as Facebook and Google self-regulate and disallow targeting for tobacco products, there are other ways in which users can be targeted advertently or inadvertently with pro-/anti- online e-cigarette policy discourse. For instance, web-based news platforms use machine learning techniques to create a curated and personalized list of news articles for every user in real-time. At an individual level, exposure to such personalized and homogenous information that conforms to user beliefs/attitudes, and limits exposure to belief/attitude challenging information, also known as the filter-bubble hypothesis (Nikolov, Oliveira, Flammini, & Menczer, 2015). This implies that social media users who engage with pro-tobacco content, in general, are possibly more likely to be exposed to similar information from pro-tobacco websites which include anti-regulatory discussions by pro-tobacco groups, especially when new regulations are under debate. Future research can explore this possibility and examine ways in which social media engagement of users interacts with attitude consistent/non-consistent information to create support for e-cigarette regulations.

FDA, the U.S. tobacco regulatory authority, is yet to introduce policies regulating online tobacco-related content (F.D.A., 2016). Presently, it is possible to create a Facebook or Twitter page to promote a group, product or idea and implicitly promote tobacco use (Hopkins, 2017). More research is needed on the types of communications on these sites that may reduce support or strengthen support for. Because more tobacco policy-related messages originate from individual social media users than public health agencies (Cole-Lewis et al., 2015), it is

also critical to identify social media users engaging with tobacco content online or communicating a pro-tobacco stance, to develop tailored interventions for tobacco policy education and awareness. A social media tobacco education campaign, in that sense, can afford high flexibility and control in real-time.

6.1. Limitations

The present study should be interpreted in the light of its limitations. First, given differences in the sample with and without complete data, these findings might not generalize to people with very high social media use, and/or to users of other social media platforms. Twitter is unique in terms of its follower model that does not warrant reciprocity to follow another user, and also offers flexibility for users to define their audiences (Bruno & Burgess, 2015; Bruno & Moe, 2014). For instance, at a macro level, Twitter hosts conversations initiated by the individuals or institutions using user or company generated hashtags. At an interpersonal level, offers features such as personal mentions/replies to facilitate personal dialogue. Future studies could replicate this research with users of other social media platforms and populations. Second, the cross-sectional data limit causal implications. It is possible that those individuals with higher engagement with e-cigarette related information are a part of online networks that are more opposed to government regulation in general. Future research should explore the interaction of overall sentiment toward government regulation and e-cigarette regulations to better contextualize these behaviors. It is quite plausible that the relationship between anti-e-cigarette policy regulations and engagement with tobacco-related content online is bidirectional or that anti-e-cigarette policy regulations lead to engagement with tobacco-related content (e.g., those with prevailing negative attitudes toward e-cigarette policy regulations might be motivated to engage with like-minded peers on social media). However, theoretically, we know that online engagement is strongly associated with attitudes and behaviors (Soneji et al., 2018), which supports our approach of examining this association of engagement leading to attitudes (Freeman, 2012). Future research should consider using longitudinal data to establish long-term and causal links between engagement and support for tobacco regulations, although this research can be defended from the perspective of face validity and diversity in sample (vs. a student sample). We also do not know of what kind of tobacco content users engaged with. This limits interpretability of our findings. It is possible that participants engaged with social media content that was more anti-tobacco than pro-tobacco. Future work can investigate effects of engagement with types of tobacco content to clarify these mechanisms in greater detail. Given evolving consensus about the actions that account for online engagement with tobacco-related information (e.g., Carah & Angus, 2018; Carah & Shaul, 2016), some of the items representing the online engagement pertain more generally to tobacco/nicotine products whereas some other refer to e-cigarettes in particular. While e-cigarette are tobacco products as per FDA guidelines, it is possible that participants engaged with information about other nicotine products, besides e-cigarettes. Lastly, the study sample is non-representative of U.S. population, which limits generalizability of the findings.

7. Conclusion

Engagement with online tobacco content is a potential public health issue. It is negatively associated with support for e-cigarette regulation. Given regulatory gaps related to online tobacco content, tailored online tobacco education campaigns will be needed to counter misinformation and encourage formation of more supportive policy attitudes.

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Conflict of interest

All authors of this article declare they have no conflicts of interest.

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