Influence of legislations and news on Indian internet search query patterns of e-cigarettes

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INTRODUCTION

Tobacco is the leading cause of preventable deaths and often consumed in smoked form. In India, it is reported to be mostly used in smoking forms — cigarette, beedi, cigar, cheroots and other indigenous forms. The products of combustion of tobacco, in any form, are known to contain more than 4000 chemical constituents and are

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more harmful than the smokeless form.[1] The smokeless form of tobacco, till the last decade, was available only in chewing and snuff form. In 2005, a new form of nicotine delivery system called electronic nicotine delivery system (ENDS) commonly known as e-cigarette, was launched and marketed globally. Since its initial design, numerous modifications have been carried out by the creative users, often collaborating through online forums. Since 2008, newer delivery system called “vapers” (short form of “vaporizer”) was introduced. Essentially in all these models tobacco extract unlike in combusted forms, is vaporized or atomized by use of controlled heat through batteries or chemical process.[3] The resultant vapor has varying concentrations of nicotine and is supposedly contains less number of carcinogenic components and reduced number of combustion-related products such as tar and carbon monoxide. There is an extensive debate on the benefits and ill-effects of ENDS.[4] Although ENDS are reported to be an effective nicotine harm reduction tool, they are believed to still have harmful effects of inhaled forms of tobacco.[4]

In 2014, the Eurobarometer Survey of all 28 European Union states reported that rate of tobacco vaping (process of using vaporizers) among current smokers was highest in the United Kingdom (11%) followed by France (8%), Denmark and the Netherlands (both 7%) and rate of vaping among ex-smokers was highest in the United Kingdom (8%), Ireland (6%) and France (6%).[3,5,6] Current tobacco smokers in India are estimated be around 108 million and the exact number of ENDS user is not known. India lacks structured data on the exact users of ENDS and this would be helpful to formulate tobacco control policies.

ENDS has been reported to be a potential oral health concern. They supposedly induce oxidative/carbonyl stress through protein carbonylation leading to inflammation and DNA damage. This leads to “a state of irreversible growth arrest which re-enforces chronic inflammation” in oral epithelial tissues resulting in oral lesions, akin to regular cigarette smoking.[7,8]

Internet-derived data such as Google searches have been successfully utilized to address many public health data gaps, in terms of behavioral outcomes in situations where use of conventional survey methods is difficult or expensive. Recent literature show a plethora of studies that provide insight into specific search terms. Such “data” has been used to estimate infectious disease epidemics, to track tobacco or emerging products such as ENDS, to study mental illness, and to analyze cancer-related information seeking.[8-13] Examining and studying the content of Google searches can arguably reveal the searcher’s thoughts. A vast majority of searches of commercial product could be viewed as a reflection of seeking information about the product or an attempt for purchasing a particular product and thus is indirectly consumption driven or drives consumption.[14]

Indian government policies and legislations in regulating the manufacture, distribution, sale and consumption of tobacco are aimed at bringing changes in the patterns of tobacco usage. There are sufficient reports in the literature supporting and refuting the changes heralded by the Indian tobacco legislations.[15] The aim of this manuscript is to study the Google-based, information-seeking behavior of Indians in respect to ENDS over a period of 4 years (48 months) and study the changing search trends based on legislative changes.

METHODS

Monthly aggregated search query raw volumes with the search terms “E-cigarette” and “Vaping,” as well as all related terms, originating in India were collected from September 1, 2012, through to September 1, 2016, using Google Adwords search (www.adword.google.com). Google Adwords is a publicly available index of search activity for specific search terms or group of terms in a defined geographical area. It also includes searches from Google’s partner engines. This would collect all related search items such as ecig/s, e-cig/s, e cig/s, electroniccigarette/s, e cigarette/s, or e-cigarette/s and vape/s, vaper/s, or vaping. It included searches such as what are?; Best; where to buy?; cost of?. Aggregate details regarding the devices and cities in India with the largest search volumes were also obtained.

All collected data were entered appropriately and analyzed using Social Package for Statistical Services, version 20 (SPSS, IBM, IL, USA). Descriptive statistics are presented for the predictor and outcome variables. The total search volume (TSV) of all terms was calculated as ENDS TSV. The dates of passing of tobacco legislations during the study were obtained and are listed in Table 1. To evaluate the impact of legislation, the month of implementation was taken as “Event month” and 1 month preceding as “pre-event month” and the following month defined as “post-event month”. All other months were considered as normal. Comparison of the mean TSV with normal (1-month before/after pre- and post-events) with the pre-event, post-event and events month were performed using analysis of variance (ANOVA).
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Table 1: Indian tobacco legislations effected during the study period

| Ministry                                      | Communication number | Dated             | Effective date       | Details                                                                 |
|-----------------------------------------------|----------------------|-------------------|----------------------|-------------------------------------------------------------------------|
| Health and family welfare                    | GSR 708(E)           | September 21, 2012 | October 2, 2012      | Display of tobacco products in films and TV                             |
| Health and family welfare                    | GSR 724(E)           | September 27, 2012 | April 1, 2013        | Health warnings in tobacco product packaging                            |
| Health and family welfare                    | GSR 739(E)           | September 24, 2015 | September 24, 2015   | Increase in space for health warnings in tobacco product packaging       |
| Juvenile justice (care and protection of children) | 2 of 2016            | December 31, 2016  | January 1, 2016      | Sale/distribution of tobacco to minors                                  |
| Health and family welfare                    | GSR 727(E)           | October 15, 2014   | April 1, 2016        | Increase in space for health warnings in tobacco product packaging       |

This study was conducted using a quasi-experimental design to examine raw volumes in Google search queries, in Google and partner search engines around Indian legislations. Time series analysis allows the comparison of outcome measures before and after the implementation of an intervention, as described previously. This method can be safely employed to study the effects of the introduction of new tobacco control policies on ENDS search. Time series analyses, using Google’s relative search volume (RSV), have been previously used to measure the impact of tobacco control policies on smoking prevalence in Australia, the Netherlands and Belgium.\(^{[14]}\) The model built also attempted to test the impact of the “event” on the TSV.

To eliminate the bias arising due to searches happening due to “sensational news,” 10 high relevance (as determined by Google page rank algorithm) news pieces from Indian newspapers were identified using Google news archives [Table 2] and the months were listed out. If the news was reported in the last days of the month, the following month was also listed, as the reported news can have an impact in the following month also. The influence of this was also studied via the model.

The normality of distribution of this ENDS volume was studied using Shapiro–Wilk test. The data were then tested for seasonal variations. If variations were encountered, we adjusted for it. Time series modeler analysis was carried out with the (i) event (ii) news pieces (iii) news and legislations together. Time series analysis using expert modeler was done. This procedure is performed in three phases: identification, estimation, and diagnosis/forecast. We excluded the last stage of such model as in the present study we did not aim to forecast TSV.

In the identification phase, auto correlation function (ACF)\(^{[14]}\) and partial ACF (PACF)\(^{[17]}\) plots of the data were examined to see which patterns are observed in the data. The ACF plot is a bar chart of the coefficients of correlation between a time series and lags of itself.\(^{[19]}\) The PACF plot is a bar chart of the correlation coefficients between the series and lags of itself that are not explained by correlation at all lower order lags.\(^{[17]}\) Based on the visual inspection of the ACF and PACF, the tentative model was finalized. In the estimation phase, the tentative model was fitted to the data series to determine the fit of the model. Extra autoregression (AR) terms were added to make sure that no terms were left out of the model. In the diagnosis phase, the best fitting model (as chosen by suggestion and fit) was identified.

Autoregressive integrated moving average (ARIMA) or The autoregressive fractionally integrated moving average model type is the most commonly used model for time series assessment. It is listed using the standard notation of ARIMA \((p, d, q) (P, D, Q)\), where \(P\) is the order of auto-regression, \(d\) is the order of differencing (or integration), and \(q\) is the order of moving-average, and \(P, D\) and \(Q\) are their seasonal counterpart.\(^{[18]}\) Based on, residual ACF and PACF, and the final model would be identified and used for further analysis.

The other common model is Winter's additive model,\(^{[19]}\) which is appropriate when the data follows a linear trend and a seasonal trend that is not dependent on the level of series. It is usually accounted by the smoothing parameters of level, trend and season. This procedure is very similar to an ARIMA model with zero orders of AR, one order of differencing, one order of seasonal differencing, and \(P + 1\) orders of moving average, where \(P\) is the number of periods in a seasonal interval (for monthly data, \(P = 12\))

Table 2: News pieces (according to relevance as obtained from Google news archives during study period from India)

| S. No | Year | Date of News | News content                  |
|-------|------|--------------|-------------------------------|
| 1     | 2016 | June 30     | Kerala government bans E-cigarette |
| 2     | 2016 | March 16    | E-cigarette ban all over India |
| 3     | 2014 | October 29  | Central minister proposes to ban E-cigarette |
| 4     | 2014 | February 5  | E-cigarette sale ban in Air India |
| 5     | 2016 | July 24     | Drug controller notice served regarding E-cigarette |
| 6     | 2015 | May 30      | Maharashtra issues notice |
| 7     | 2014 | October 31  | Ban all over India |
| 8     | 2016 | August 8    | Claims to be safe |
| 9     | 2015 | December 8  | May harm lungs |
| 10    | 2016 | April 18    | First arrest for selling |
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The best model was chosen and used after verification of ACF and PACF, for all three situations. All model descriptions, fit and events influencing the model were presented. \( P \leq 0.05 \) was considered statistically significant.

RESULTS

As per the criteria, three search terms emerged – they were “vape,” “ecig” and “ecigarette.” All associated terms were included for the study. The sum of total volume of search (TSV) of ENDS was obtained. During the 48 months study period, the monthly TSV was also obtained. The mean ± standard deviation for search criteria for “vape” was 3981.67 ± 4828.99 (range: 110–18,100; median 1300; inter quartile range: 480–6300); “ecig” was 212.92 ± 69.31 (70–390) and for “ecigarette” was 18,079.17 ± 3707.32 (12,100–33,100). The overall TSV was 22,273.75 ± 6784.01 (12,310–40,510). The Shapiro–Wilk test for normality indicated a normal distribution of TSV data.

On an average, per month, 13,712 ENDS-TSV search were performed from desktop devices, 7652 from mobile/smart phones and 546 from tablets. The desktop search frequency decreased from 2012 to 2016 while smartphone searches increased. The number of mean searches per month (in brackets) from major cities were as follows: New Delhi (3,128); Bengaluru (2,733); Mumbai (1,900); Chennai (1,359) and Hyderabad (1,286). The ANOVA test failed to find statistically significant difference in TSV between, pre-event, event, post-event and normal months [Table 3]. However, the impact of news was statistically significant (\( P = 0.001 \)) [Table 4].

The mean TSV was 22,273.75 ± 6784.02 searches, with a median (interquartile range [IQR]) of 20,375 (IQR=6265). The overall TSV was 18,079.17 ± 3707.32 (12,100–33,100). The Shapiro–Wilk test for normality indicated a normal distribution of TSV data.

Table 3: Effect of Indian legislation on total search volume of electronic nicotine delivery systems during the study period

| Event Time | Mean±SD of TSV | 95% CI | Minimum | Maximum | \( P \) |
|------------|----------------|--------|---------|---------|--------|
| Pre-event month | 20,196.00±6540.91 | 12,074.39 | 28,317.61 | 12,560 | 28,170 | 0.640 |
| Event month | 20,620.00±7794.49 | 10,718.36 | 30,521.64 | 12,310 | 30,520 | 0.001 |
| Post-event month | 26,074.00±8137.20 | 15,970.33 | 36,177.67 | 15,000 | 33,530 | 0.001 |
| Normal period | 22,215.00±8633.21 | 13,155.00 | 31,275.00 | 12,630 | 34,510 | 0.001 |

SD: Standard deviation, TSV: Total search volume, CI: Confidence interval

The independent variable, the legislation-pre-event, event and post-event month TSV is not shown to be a better indicator of the effect barring for post-event month of 2nd legislation in the study period. Time series modeler offers a number of different goodness-of-fit statistics; we opted only for the stationary R\(^2\) value, which was 0.440 (This statistic provides an estimate of the proportion of the total variation in the series that is explained by the model), indicating a good fit in the model. The Ljung-Box statistics is an indicator of specificity of the model. A significance value ≤0.05 indicates that there is structure

| News | Mean±SD | 95% CI for mean | Minimum | Maximum | \( P \) |
|------|---------|----------------|---------|---------|--------|
| Yes | 27,841.82±8207.16 | 22,328.17 | 33,355.47 | 18,570 | 40,510 | 0.001 |
| No  | 20,618.38±5393.08 | 18,820.24 | 22,416.52 | 12,310 | 33,530 | 0.001 |

SD: Standard deviation, CI: Confidence interval
in the observed series which is not accounted for by the model. The value of 0.396 obtained in this model is not significant, indicating that the model is correctly specified and there were no outliers. The ARIMA model parameter describing more of the predictor event is listed as Table 6.

**News pieces**

The ACF and PACF are shown in Figure 5 and model fit is shown in Figure 6. For influence of the news pieces, the best time series modeler was the ARIMA (0, 1, 1) (0, 0, 0). The Model fit statistics was estimated using stationary $R^2 (=0.462)$ and Ljung-Box statistics of 9.909 with $P = 0.907$ and no outliers but with one predictor event—a news piece related to the Pan-India Ban on ENDS in October/November 2014. The ARIMA model parameters showed a lag1 with Estimate of 0.499, $t = 3.348$ and $P = 0.002$ while with the predictor event, the estimate showed 16359.55, $t = 4.843$, $P \leq 0.001$.

### Table 5: Seasonal factor as observed in raw data of total search volume of electronic nicotine delivery systems

| Seasonal factor (%) |       |
|---------------------|-------|
| January             | 104.4 |
| February            | 91.5  |
| March               | 90.7  |
| April               | 116.5 |
| May                 | 109.9 |
| June                | 98.7  |
| July                | 99.0  |
| August              | 81.2  |
| September           | 100.7 |
| October             | 88.8  |
| November            | 106.0 |
| December            | 112.6 |

### Table 6: Effect of predictor event in Indian legislation autoregressive integrated moving average model

| Model Parameter | Lag | Estimate  | SE  | $t$   | $P$  |
|-----------------|-----|-----------|-----|-------|------|
| Difference      | 1   |           |     |       |      |
| Moving average  | Lag 1 | 0.432     | 0.136| 3.184 | 0.003|
| Numerator       | Lag 0 | 15,694,660| 3431.743| 4.573 | 0.000|
| Difference      | 1   |           |     |       |      |

SE: Standard error

**Figure 1:** The total search volume of electronic nicotine delivery system in the study period, by month

**Figure 2:** The total search volume during study period after accounting for seasonal variations
Legislation and news
The ACF, PACF and model are shown in Figures 7 and 8, respectively. When the legislations and news events were combined, the best model was Winter’s additive model. The stationary $R^2$ was 0.721, more closer to 1 than any other model with Ljung-Box Q statistics of 20.632 and significance of 0.149, with no significant predictors and outliers. The exponential smoothing model parameter revealed alpha (level) estimate as 0.5 with $t = 3.6$ at $P = 0.001$, the gamma (trend) as $0.43 \times 10^{-5}$, $t = 0.73 \times 10^{-5}$ ($P = 1$) and delta (season) at $0.16 \times 10^{-5}$, $t = 0.66 \times 10^{-5}$, $P = 1$.

DISCUSSION
The use of ENDS as a substitute of common nicotine delivery system—the cigarette, has been highly debated. Few audits have revealed that it is an excellent harm reduction tool while others have pointed out that ENDS just serves as another tool or mode of tobacco addiction. Based on multiple factors including the high cost associated with the ENDS, the usage of ENDS among Indians is largely limited. As the sale and use of ENDS is largely unmonitored, the exact number of ENDS users in India cannot be estimated. With recent legislative changes and government regulations, the sale and usage of ENDS are also restricted. Given the scenario, any data on the number of ENDS users will help policy makers to frame appropriate policies. In addition, think-tanks and tobacco harm reduction supporters are coming up with suggestions to promote sale and use of ENDS in the Indian context.

Given the complex nature of ENDS supply chain in India, our aim was to undertake this study to identify the number of searches related to ENDS by Indians in the “Google” search engine, which currently holds the position as the most favored search engine in India. Search volumes have been used to study tobacco consumption pattern including ENDS to draw meaningful comparisons and conclusions. The previous studies employed Google trends, which has been updated. The up-to-date version does not offer comparison features. In addition, the RSV is a function of the total number of searches in a defined period of time. As this is fluctuating over large period of time, the RSV of a group of particular search term, progressively decreases, provided the TSV is nearly stable, while the number of searches increases. This would create a negative slope. This study employed the TSV from Google Adwords which is a measure of the total number of searches and is not a function of any other parameter. However, the present manuscript relies on the fact that any search related to ENDS is predominantly motivated by the desire to seek, know or buy ENDS. Although a small proportion would be a knowledge seeking pattern, cessation or side effects, such numbers are bound to be small, as identified by previous studies in the western population. The last update of Google (July 2016) trends rendered the comparison across “categories” impossible and rendering comparison of our findings with previously published literature, next to impossible.
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We observed a seasonal variation in number of searches for ENDS. The different peaks as observed in the raw TSV [Figure 1 and Table 3] indicate a seasonal variation. After accounting for the same, three instances of peak were observed. The month of May 2013, 2014 and 2016 saw peaks while May 2015 saw a dip in TSV. The month of May corresponds to “Anti-tobacco Day” wherein there is a huge promotion of tobacco cessation programs while traditionally, December sees a lot of people assuming “new year resolutions” to quit tobacco or step down consumption as seen in December 2014.[14] Probably these episodes are partly responsible for the increase in TSV. Generally, 2016 saw an increase in TSV activity consistently across all months, the reason for which we could not decipher. We assume that the sudden spurt of interest in ENDS in 2016 is the increased promotion of ENDS as an alternative to traditional cigarettes, though no visible promotion were observed in main stream media.

The legislative changes, haven’t evoked a change in TSV as observed in our model [Figure 4], with the exception of pictorial warnings on pack, implemented from April 1, 2013. Though there is a visible, observable, difference in pre/post and event month, it was not statistically significant, as observed in epidemiological studies.[15] The legislation regarding pictorial warning on tobacco packagings, has caused a statistically significant difference in the search pattern of ENDS, especially, even after one month of proclamation of the law. In the month of April 2013, the TSV was 12,600 which increased to 33,530 in the postlegislation (pictorial warning on cigarette) month. This could be interpreted as a knee jerk reaction by users to pictorial warning and the search for ENDS increased. Such a sudden “shock effect,” that persists for shorter duration (4–8 weeks) and in large volume is not new in tobacco cessation literature.[14,25-29] Such an effect has been known to weaken quickly when the population adjust to newly imposed situations.[14,30,31]

On the other hand, the news of current [Table 2] events did result in increase in TSV [Table 4]. However, this was not sufficient enough, to cause a significant difference to disrupt the model, when considered individually. The only notable exception was when the health minister mulled for a pan-Indian ban on ENDS in October 2014. When the models were combined [Figure 8], we were not able to identify legislative or news events that resulted in a significant change. Such legislation and subsequent deliberations in media have been shown to increase tobacco cessation program searching behavior as well as looking for alternatives. However, our results predict that such effects may be short lived. This is in agreement with prior reports from the Netherlands.[14] In addition, it must be interpreted with caution as only the select high impact “news” were considered for inclusion in the model. While there has been a consistent outflow, all spills of news for ENDS in media over the study period was not accounted.

Figure 5: Autocorrelated and partial auto correlated function for the model accounting studying the effect of news pieces in the study. SAS - Seasonal Adjusted Model

Figure 6: The fit of the model and effect of news pieces in the study. SAS - Seasonal Adjusted Model; UCL - Upper Confidence Limit; LCL - Lower Confidence Limit
Oral health research at molecular level shows noxious changes very similar to conventional tobacco products\[^{[7,8]}\] while short, isolated researches show a contradicting reports of positive improvement in oral health status.\[^{[32]}\] The introduction and increasing use of ENDS among Indians are a cause of concern. There are no prior studies on the use of ENDS or related information seeking behavior of Indians. Though, the results of the study need to be interpreted with caution, it provides a basic, robust estimate and future studies can evolve from this study. Dentists need to be aware of peculiar incidences related to ENDS, such as bursting of ENDS in oral cavity and should be prepared to treat such events.\[^{[33]}\] It is believed that with newer generations of ENDS being increasingly considered as stimulators for habituation of tobacco/nicotine, dentists and allied professionals need to be aware of the trends in use of ENDS at least in the community they cater.\[^{[34]}\] With the ENDS market being projected at a compounded annual growth rate of 63.38% over the period 2013–2018, this need becomes increasingly significant.\[^{[35]}\]

**CONCLUSION**

We have presented the search query trends for ENDS in India over a 4 years period, as well as observing the interaction of tobacco-related legislations and news pieces on search volumes in the same study period. Most of the ENDS uses substances that often contain nicotine with additives but not in the form of tobacco. This form the basis of circumventing the Indian anti-tobacco regulations - mainly the cigarettes and other tobacco products (prohibition of advertisement and regulation of trade and commerce, production, supply and distribution) act, 2003, which governs the warnings on the packaging as well as regulates the advertisements of tobacco products. However, we failed to identify substantial support for this in the literature, hence remains largely anecdotal.

To the best of our knowledge, this is the first study of its kind to use the search queries related to ENDS in a developing country (India). Our study shows that though there might be minor contribution in terms of effect of legislations and news pieces on TSV, their influence is not significant. In the Indian context, based on this result we could infer that (i) search for ENDS by Indians is increasing over time; (ii) seasonal factors influence the search for ENDS (iii) one legislation-the one regarding the pictorial warning and popular news pieces influence (in a statistically significant fashion) the TSV while important policy decisions evoke a visible, statistically in-significant jump in TSV pattern. We propose that this increase in search of ENDS may translate to more use of ENDS and such trend analysis may indirectly reflect usage pattern. More detailed research is required to capture the impact of legislative changes and news items on search patterns and behavioral changes.

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**Figure 7:** Autocorrelated and partial auto correlated function for the model accounting studying the combined effect of legislation events and news pieces in the study. SAS - Seasonal Adjusted Model

**Figure 8:** The fit of the model and combined effect of legislation events and news pieces in the study. SAS - Seasonal Adjusted Model; UCL - Upper Confidence Limit; LCL - Lower Confidence Limit
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REFERENCES

1. Danaei G, Ding EL, Mozaffarian D, Taylor B, Rehm J, Murray CJ, et al. The preventable causes of death in the United States: Comparative risk assessment of dietary, lifestyle, and metabolic risk factors. PLoS Med 2009;6:e1000058.

2. Rooban T, Elizabeth J, Umadevi KR, Ranganathan K. Sociodemographic correlates of male chewable smokeless tobacco users in India: A preliminary report of analysis of National Family Health Survey, 2005-2006. Indian J Cancer 2010;47 Suppl 1:91-100.

3. Morris J, Khan AU. The Vapour Revolution: How Bottom-up Innovation is Saving Lives and Prospects for India. Reason Foundation Working Paper, August, 2016. Available from: from http://www.reason.org/files/vapour_revolution_working_paper.pdf. [Last accessed on 2016 Oct 02].

4. Ettner JF. E-cigarettes: Methodological and ideological issues and research priorities. BMC Med 2015;13:32.

5. Eurobarometer. Attitudes of Europeans Towards Tobacco and Electronic Cigarettes, Brussels: European Commission, Special Eurobarometer, Number 429; 2015. Available from: http://www.ec.europa.eu/public_opinion/archives/cbs/cbs_429_en.pdf. [Last accessed on 2016 Oct 02].

6. Andler R, Guignard R, Wilquin JL, Beck F, Richard JB, et al. Electronic cigarette use in France in 2014. Int J Public Health 2016;61:159-65.

7. Sundar IK, Javed F, Romanos GE, Rahman I. E-cigarettes and flavorings induce inflammatory and pro-senescent responses in oral epithelial cells and periodontal fibroblasts. Oncotarget 2017;7:77196-204.

8. Ji EH, Sun B, Zhao T, Shu S, Chang CH, Messadi D, et al. Correction: Characterization of electronic cigarette aerosol and its induction of oxidative stress response in oral keratinocytes. PLoS One 2016;11:e0169380.

9. Carneiro HA, Mylonakis E. Google trends: A web-based tool for real-time surveillance of disease outbreaks. Clin Infect Dis 2009;49:1557-64.

10. Ayers JW, Althouse BM, Allem JP, Childers MA, Zafar W, Latkin C, et al. Do seasons have an influence on the incidence of depression? The use of an internet search engine query data as a proxy of human affect. PLoS One 2010;5:e13728.

11. Yang AC, Huang NE, Peng CK, Tsai SJ. Do seasons have an influence on the incidence of depression? The use of an internet search engine query data as a proxy of human affect. PLoS One 2010;5:e13728.

12. Ayers JW, Ribisl KM, Brownstein JS. Monitoring of non-cigarette tobacco use using search query surveillance. Am J Prev Med 2011;40:448-53.

13. Ayers JW, Althouse BM, Allem JP, Leas EC, Dredze M, Williams RS. Revisiting the rise of electronic nicotine delivery systems using search query surveillance. Am J Prev Med 2016;50:e173-81.

14. Troelstra SA, Bosdriesz JR, de Boer MR, Kunst AE. Effect of tobacco control policies on information seeking for smoking cessation in the Netherlands: A Google Trends Study. PLoS One 2016;11:e0148489.

15. Thakur A, Shivakumar KM, Patil S, Suresh KV, Kadashetti V. A study on adolescents to assess the impact of pictorial and textual warnings on panels of smoked and smokeless tobacco products in Western Maharashtra, India. J Indian Assoc Public Health Dent 2015;13:250-3.

16. Pankratz A. Forecasting with Univariate Box-Jenkins Models: Concepts and Cases. 1st ed. New York: John Wiley and Sons; 1983.

17. Box GE, Jenkins GM. Time Series Analysis: Forecasting and Control. Revised Edition. San Francisco: Holden-Day; 1976.

18. Kohn R, Ansley A. Efficient estimation and prediction in time series regression models. Biometrika 1985;72:694-7.

19. Brockwell PJ, Davis RA. Time Series: Theory and Methods. 2nd ed. New York: Springer-Verlag; 1991.

20. Pepper JK, Brewer NT. Electronic nicotine delivery system (electronic cigarette) awareness, use, reactions and beliefs: A systematic review. Tob Control 2014;23:375-84.

21. Nutt DJ, Phillips LD, Balfour D, Curran HV, Dockrell M, Foulds J, et al. Estimating the harms of nicotine-containing products using the MCDA approach. Eur Addict Res 2014;20:218-25.

22. Zeller M, Hatakami D. Strategic Dialogue on Tobacco Harm Reduction Group. The strategic dialogue on tobacco harm reduction: A vision and blueprint for action in the US. Tob Control 2009;18:324-32.

23. West R. Electronic Cigarettes: Getting the Science Right and Communicating it Accurately. Addiction; 2014. Available from: http://www.onlinelibrary.wiley.com/journal/10.1111/%28ISSN%291360-0443/homepage/electronic_cigarettes.htm. [Last accessed on 2016 Oct 02].

24. Cavazos-Rehg PA, Krauss MJ, Spitznagel EL, Lowery A, Gruca RA, Chaloupka FJ, et al. Monitoring of non-cigarette tobacco use using Google Trends. Tob Control 2015;24:249-55.

25. Nagelhout GE, Willemsen MC, de Vries H. The population impact of smoke-free workplace and hospitality industry legislation on smoking behaviour. Findings from a national population survey. Addiction 2011;106:816-23.

26. Nagelhout GE, de Vries H, Boudreau C, Allwright S, McNeill A, van den Putte B, et al. Comparative impact of smoke-free legislation on smoking cessation in three European countries. Eur J Public Health 2012;22 Suppl 1:4-9.

27. Edwards R, Thomson G, Wilson N, Waa A, Bullen C, O'Dea D, et al. After the smoke has cleared: Evaluation of the impact of a national smoke-free law in New Zealand. Tob Control 2008;17:22.

28. Wilson N, Sertsou G, Edwards R, Grigg M, Li J. A new national smokefree law increased calls to a national quitline. BMC Public Health 2007;7:75.

29. Hackshaw L, McEwen A, West R, Bauld L. Quit attempts in response to smoke-free legislation in England. Tob Control 2010;19:160-4.

30. Hu TW, Sung HY, Kuebler TE. Reducing cigarette consumption in California: Tobacco taxes vs. an anti-smoking media campaign. Am J Public Health 1995;85:1218-22.

31. Pekurinen M, Valtonen H. Price, policy and consumption of tobacco: The Finnish experience. Soc Sci Med 1987;25:875-81.

32. Tatullo M, Gentile S, Paduano F, Santacroce L, Marrelli M. Crosstalk between oral and general health status in e-smokers. Medicine (Baltimore) 2016;95:e5589.

33. Nagelhout GE, de Vries H, Boudreau C, Allwright S, McNeill A, van den Putte B, et al. Comparative impact of smoke-free legislation on smoking cessation in three European countries. Eur J Public Health 2012;22 Suppl 1:4-9.

34. King AC, Smith LJ, McNamara PJ, Cao D. Second generation electronic cigarette aerosol and its induction of oxidative stress response in oral keratinocytes. PLoS One 2016;11:e0169380.

35. Market Report. Electronic Cigarettes, Brussels: European Commission, Special Eurobarometer, Number 429; 2015. Available from: http://www.ec.europa.eu/public_opinion/archives/cbs/cbs_429_en.pdf. [Last accessed on 2016 Oct 02].

36. Hurlin CL, Laurent G. Estimating the harms of nicotine-containing products using the MCDA approach. Tob Control 2014;23:375-84.