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

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Abstract

Background: There is a paucity of data on the use of electronic nicotine delivery systems (ENDS) in India. In addition, the Indian internet search pattern for ENDS has not been studied. We aimed to address this lacuna. Moreover, the influence of the tobacco legislations and news pieces on such search volume is not known. Given the fact that ENDS could cause oral lesions, these data are pertinent to dentists.

Methods: Using a time series analysis, we examined the effect of tobacco-related legislations and news pieces on total search volume (TSV) from September 1, 2012, to August 31, 2016. TSV data were seasonally adjusted and analyzed using time series modeling. The TSV clocked during the month of legislations and news pieces were analyzed for their influence on search pattern of ENDS.

Results: The overall mean ± standard deviation (range) TSV was 22273.75 ± 6784.01 (12310–40510) during the study with seasonal variations. Individually, the best model for TSV-legislation and news pieces was autoregressive integrated moving average model, and when influence of legislations and news events were combined, it was the Winter's additive model. In the legislation alone model, the pre-event, event and post-event month TSV was not a better indicator of the effect, barring for post-event month of 2nd legislation, which involved pictorial warnings on packages in the study period. Similarly, a news piece on Pan-India ban on ENDS influenced the model in the news piece model. When combined, no "events" emerged significant.

Conclusions: These findings suggest that search for information on ENDS is increasing and that these tobacco control policies and news items, targeting tobacco usage reduction, have only a short-term effect on the rate of searching for information on ENDS.

Keywords: E-cigarettes, India, legislation, oral health, tobacco

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Received: 16.02.2017, **Accepted:** 24.05.2017

INTRODUCTION

Tobacco is the leading cause of preventable deaths and often consumed in smoked form.[1] In India, it is reported to be mostly used in smoking forms – cigarette, beedi, cigar, cheroots and other indigenous forms.[2] The products of combustion of tobacco, in any form, are known to contain more than 4000 chemical constituents and are

Access this article online	
Quick Response Code:	Website: www.jomfp.in
	DOI: 10.4103/jomfp.JOMFP_23_17

How to cite this article: Thavarajah R, Mohandoss AA, Ranganathan K, Kondalsamy-Chennakesavan S. Influence of legislations and news on Indian internet search query patterns of e-cigarettes. J Oral Maxillofac Pathol 2017;21:194-202.

more harmful than the smokeless form.[3] 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 modifi cations 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.[9-13] 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 publically 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).

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	January1, 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)[16] 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.[16] 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.

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 all over India
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

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, $P = 12$)

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 22273.75 ± 6784.01 (12310–40510). 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 minimum TSV was 12,310 (October 2012) while the maximum was 40,510 (August 2016). The TSV was not distributed uniformly. The raw data, exhibited peaks in the month of August 2016 (40,510), July 2016 (37,210), November 2014 (34,690) and June 2016 (34,510). In addition, there were more than 30,000 TSV in the months of May 2013 (33,530), May 2016 (33,110), April 2016 (30,520) and February 2016 (30,410). Of these, May 2013 (2nd law) and May 2016 (5th law) were post-event months for the legislations depicted in Table 1 while April 2016 (5th law) was an event month. The raw TSV format is attached as Figure 1. There were three major peaks observed. The seasonal variation estimation is given in factor (of percentage) in Table 5. Seasonally, December appears to have higher TSV, followed by April, May and June. A seasonal variation existence was observed and nullified to use in further models as seasonal adjusted series of TSV [Figure 2].

Legislations only

Time series analysis was performed employing expert modeler. In the identification phase, visual inspection of the ACF and PACF [Figure 3], initial autoregressive (AR) was determined as a tentative model. In the estimation phase, we identified that the best fitting model was the ARIMA (0, 1, 1) (0, 0, 0) and this final model was used for further analysis [Figure 4].

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

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

	Mean±SD of TSV	95% CI		Minimum	Maximum	P
		Lower	Upper			
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±7974.49	10,718.36	30,521.64	12,310	30,520	
Post-event month	26,074.00±8137.20	15,970.33	36,177.67	15,000	33,530	
Normal period	22,215.00±8633.21	13,155.00	31,275.00	12,630	34,510	

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

Table 4: Effect of Indian news on total search volume of electronic nicotine delivery systems during the study period

News	n	Mean±SD	95% CI for mean		Minimum	Maximum	P
			Lower	Upper			
Yes	11	27,841.82±8207.16	22,328.17	33,355.47	18,570	40,510	0.001
No	37	20,618.38±5393.08	18,820.24	22,416.52	12,310	33,530	

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

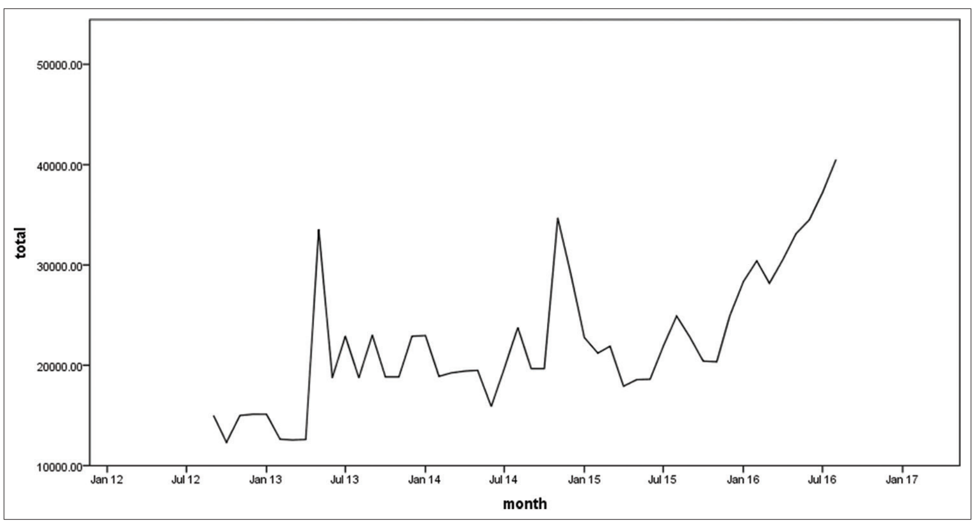

Figure 1: The total search volume of electronic nicotine delivery system in the study period, by month

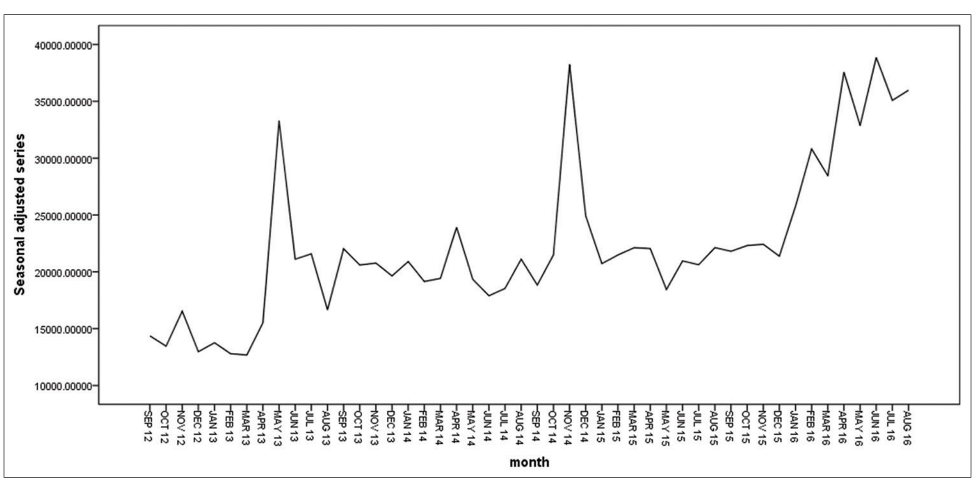

Figure 2: The total search volume during study period after accounting for seasonal variations

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 0.43×10^{-5}, $t = 0.73 \times 10^{-5}$ ($P = 1$) and delta (season) at 0.16×10^{-4}, $t = 0.66 \times 10^{-5}$, $P = 1$.

DISCUSSION

The use of ENDS as a substitute of common nicotine delivery system– the cigarette, has been highly debated.[4] 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.[20-24] Based on multiple factors including the high cost associated with the ENDS, the usage of ENDS among Indians is largely limited.[3] 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.[3] 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.[3]

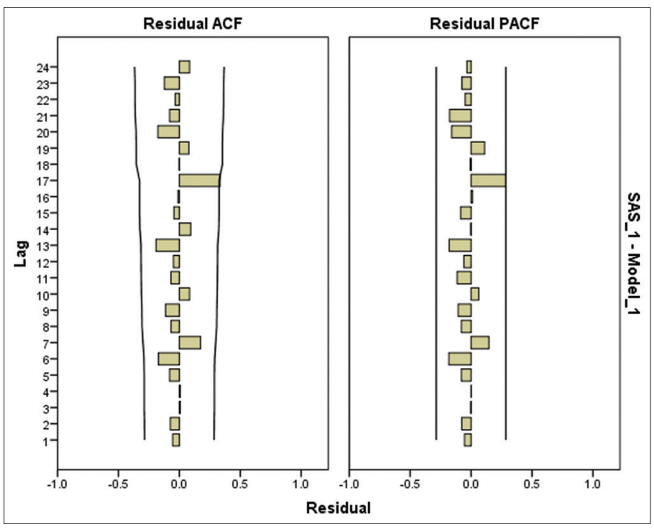

Figure 3: Autocorrelated and partial auto correlated function for the model for studying the effect of Legislation. SAS - Seasonal Adjusted Model

Given the complex nature of ENDS supply chain in India, our aim was 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.[12-14] The previous studies employed Google trends, which has been updated. The up-to-date version does not offer comparison features. In addition, the RSV [Figure 9] is a function of the total number of searches in a defined period of time.[12-14] As this is fluctuating over large period of time [Figure 9], 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.[14] 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.[14] 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.

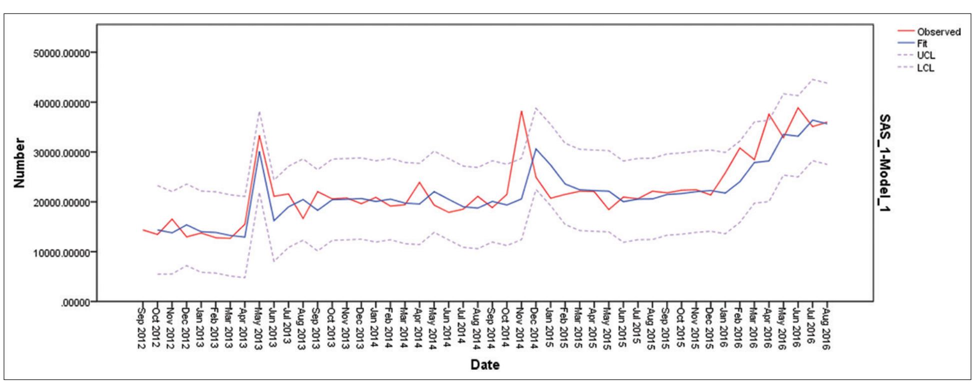

Figure 4: The fit of the model and effect of legislation "events" in the study. SAS - Seasonal Adjusted Model; UCL - Upper Confidence Limit; LCL - Lower Confidence Limit

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.

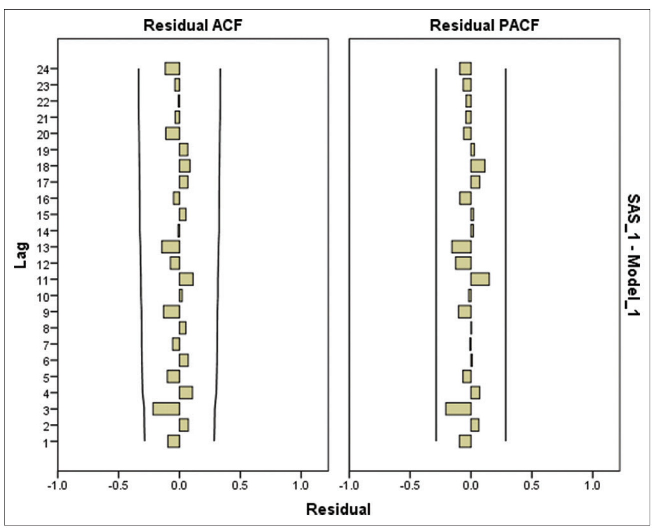

Figure 5: Autocorrelated and partial auto correlated function for the model accounting studying the effect of news pieces in the study. SAS - Seasonal Adjusted Model

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.

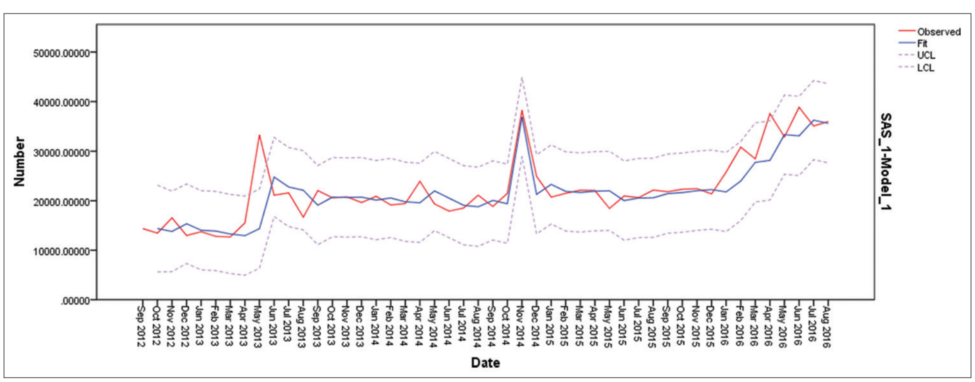

Figure 6: The fit of the model and effect of news pieces in the study. SAS - Seasonal Adjusted Model; UCL - Upper Confidence Limit; LCL - Lower Confidence Limit

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]

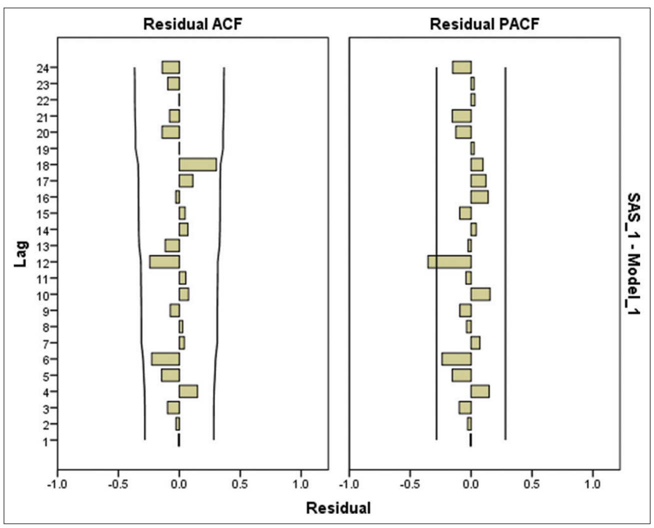

Figure 7: Autocorrelated and partial auto correlated function for the model accounting studying the combined effect of legislation events and news pieces in the study. SAS - Seasonal Adjusted Model

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.

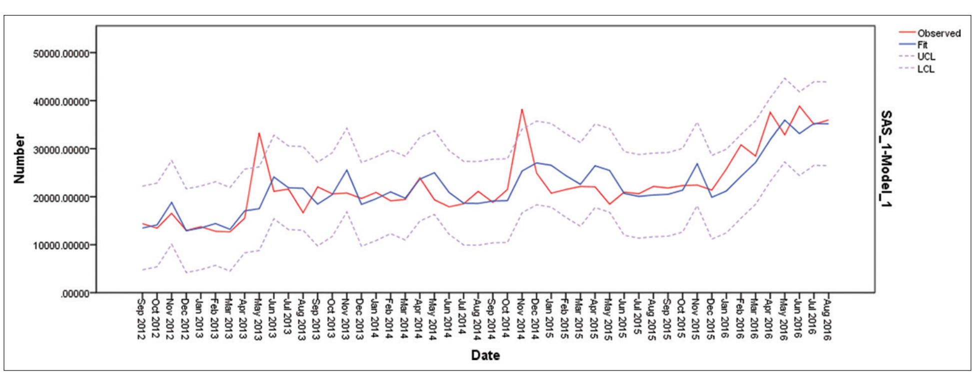

Figure 8: The fit of the model and combined effect of legislation events and news pieces in the study. SAS - Seasonal Adjusted Model; UCL - Upper Confidence Limit; LCL - Lower Confidence Limit

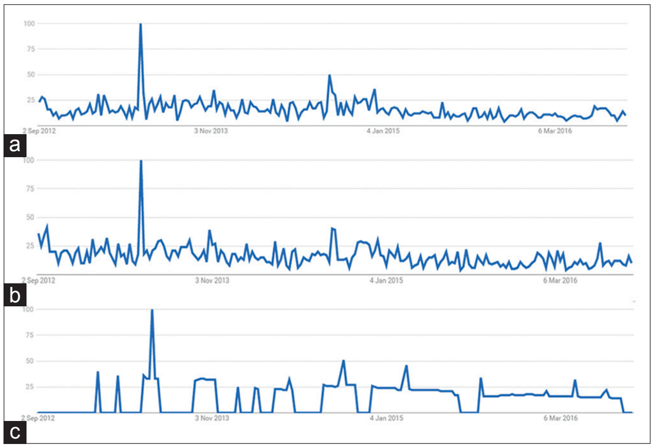

Figure 9: The relative search volume of electronic nicotine delivery system in the study period using Google trends, (a) in all categories, (b) in smoking cessation category, (c) in news pieces

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

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