Global Media Journal-Indian Edition; Volume 14 Issue 2; December 2022. ISSN:2249-5835

"SDG 2030: Analysis of Political Tweets Using Deep Learning Approach"

Dr Ashwini Ramesh
ICSSR Post-Doctoral Fellow
Department of Mass Communication and Journalism
Bengaluru City University
Bengaluru, Karnataka

Author Note

Dr Ashwini Ramesh https://orcid.org/0000-0003-1363-4507
Author Correspondence: Dr Ashwini Ramesh
Mobile: 9739893248
Email: ashwini.ramesh95@gmail.com

Funding and Acknowledgment: The Scholar Dr Ashwini Ramesh is the awardee of ICSSR Post-Doctoral fellowship. This research paper is largely an outcome of the Post-Doctoral Fellowship sponsored by ICSSR. However, the responsibility for the facts stated, opinions expressed, and the conclusions drawn is entirely of the author.

Abstract

New media technologies have democratized information and communication today. With large scale and transparent discourses, personified tweets have strengthened political institutions, inclusivity and sustainability communication. Sustainable development goals (SDG) state that inclusive societies are possible only through peace and harmony. Goal 16 describes inclusive society as a space where justice is for all and accountable. NITI Aayog report stated that no sustainable development can take place without a peaceful society that is in isolation from violence and fear. However, recent communal violence in Udaipur, and the consequential attack and counterattack of Indian political leaders through tweets on this and other socio-economic developmental issues, and a series of natural disasters have indicated an ineffective promotion and implementation of SDGs. Through big data environment, political leaders have an influential power on citizens in mobilizing them for public participation. Thus, the objectives of the study are – 1) to analyze tweets of Indian politicians in a politically vulnerable period, and 2) to analyze social indicators like peace, harmony, and inclusivity in the tweets of Indian political leaders. Sentiment analysis was performed on the tweets of top eight followed Indian political leaders using pre-trained BERTweet model achieving an accuracy of 0.9918. Findings indicate minimal indulgence in spreading 'non-violence' and 'sustainability' tweets. Echo chambers are created with sentiment polarity of positive tweets from ruling party leaders in comparison to the opposition. Study suggests integrating tweeting priorities of Indian political leaders with SDG – 2030.

Keywords: SDG, political tweets, Goal 16, Udaipur, Python, India

Introduction

The Indian media industry has seen a revolutionary change in the past decade. In 2011, anti-corruption movement lead by team Anna introduced social media in India. Since then it has become a powerful communication tool. Social media has democratised public interaction (Dahlgren, 2005) where information exchange is direct and continuous. This paradigm shift has facilitated political leaders to engage in large scale and transparent online discourses. Social media has strengthened political institutions and citizen empowerment by bridging the gap between government and society.

In 2015, United Nations General Assembly adopted Sustainable Development Goals (SDGs) 2030 where the agenda is to end inequality, poverty, hunger, climate change, and development of inclusive societies. SDGs aim to stabilize economic, social and environment sustainability. These Global Goals calls for unified action adopted under 17 goals, 169 targets and 300 indicators. NGOs, politicians, government and non-government organisations, business sectors, and the public are reckoned to derive an action plan to implement SDGs focusing on planet, people and prosperity (Schramade, 2017).

Goal 16 of SDG defines inclusive society as a space where justice is for all and accountable. It envisions reducing all forms of violence and its associated deaths to build strong institutions of global governance. However, the major challenge is to identify torchbearers of SDG who will be the leaders to implement them in context-specific goals (Ali et al., 2019). Political leaders act as critical agents in assisting e-governance (Vakeel and Panigrahi, 2018). Political leaders can become influencers to promote SDGs (Grover et al., 2021).

Thus, the present study has considered Twitter usage of political leaders for analysis. Twitter is a microblogging social network platform and is popular among all age groups of people. Personified political tweets have become promoter of inclusivity and sustainability communication (Heiner, 2018). Digital affordances on Twitter have conceptualized

participatory communication (Enli and Skogerbo, 2013). There is an evidence of citizen empowerment when voters directly interact with their political leaders. It also becomes important to understand the stance of political leaders on issues of significance, and the way they treat these issues on popular social media tool, thereby influencing the public.

Thus, the first part of the study presents review of literature followed by rationale of the study. This gives pathway to describe research design with specifications on sentiment analysis, research objectives, data collection, pre-processing techniques, and research method. The second part of the study presents data analysis and results followed by conclusion. The study is concluded with practical and scholarly implications to define better communication strategies for using Twitter to promote sustainable living.

Related Literature

Menendez et al. (2021) studied #WorldEnvironmentDay on Twitter wherein the authors performed sentiment analysis using Python to find public opinion towards sustainable development goals. Findings showed that sustainable environment as a goal on Twitter stood negative. Climate change, deforestation, tree falling, pollution, biodiversity and industrialization are not positively tweeted by the masses indicating a further downfall of SDG. Positive tweets included public health. Neutral tweets were on healthy lifestyle. Authors suggested that NGOs, policymakers, institutions, social associations, and even United Nations should use world renowned days like #WorldEnvironmentDay to popularise SDG and improve public perception on them. Sciandra et al. (2021) analysed information and action on 'UN Agenda 2030' on Twitter data using supervised machine learning approach. Findings showed that tweets on sustainable environment was underrepresented, and explained the concept of clicktivism/ slacktivism. They said that retweets need no effort and are rampant without having to know about the content being retweeted. Authors emphasise on users retweeting without responsible commitment to act towards the issue. Study suggests orientation concerning collective and individual actions via shared practices

towards SDG- 2030. Authors emphasised that positive actions are promoted only in certain tweets indicating that a few certain percentage of users are able to connect global challenges with local problems. A comprehensive study by (Grover et al., 2021) analysed tweeting behaviour of political leaders across the globe. They stated that political leaders are the changemakers and have an ability to enrich understanding and knowledge of the public towards SDG. Study elaborated on countries specific SDG and achieving it based on their economic status like developed, developing or countries in transition. Findings revealed that European and African countries are ahead in promoting SDGs followed by Asian countries. In fact, developing economies like Chile, India and Uganda have higher SDG scores as compared to developed economies like USA, Germany, and Singapore. In the improvement scores of twitter engagement among political leaders on SDG, developed economies showed 25.88% while developing economies showed 21.78%.

In addition, elaborating on implementation of SDG, (Allen et al., 2017a) talked about SDG not being based on national values and priorities, unable to connect at local level (Jabbour et al., 2019b), and its communication strategies not reaching the lowest strata of society (Wu et al., 2018).

All these studies elaborate on ineffective implementation of SDGs. They examine the importance of communication strategies and the need for government authorities to take initiatives in promoting SDGs. However, there is a lack of academic literature in understanding the extent to which tweeting on SDGs take place among the top followed political leaders in a country-specific analysis. Earlier studies have limited to user engagement and SDG taxonomies like tweets on World environment day, Yoga day or World health day. SDG priority among Indian political leaders in a socially and politically vulnerable period is yet to be academically explored.

Rationale of the study

From the related literature, rationale of this study is to analyse tweets of top followed Indian political leaders with a special emphasis on SDGs. As explained in the above section, there is still a knowledge void in examining the tweeting patterns of influential political leaders in times of crisis. To fill this academic vacuum, the present has chosen a vulnerable period like communal disturbance in Udaipur, bypoll results in Punjab, Andhra Pradesh, Jharkhand and Delhi, natural calamities like floods in Assam, landslide in Manipur, and earthquake in Afghanistan. Tweeting priorities in such critical times should be investigated because Twitter users are diverse and can be easily conditioned by influential political leaders. Spreading non-violence through tweets, and engagement in sustainability communication through popular social media platforms helps to build awareness on significance of SDG. Twitter discussions and trends help to spread messages conveniently as users follow powerful and influential thought leaders on social media (Sedera et al., 2017). Since data on Twitter is voluminous and unorganised, it is advisable to retrieve them using machine learning techniques for highest possible accuracy (Plummer et al., 2017). The present study uses NLTK on Python for data retrieval and analysis. On the basis of Goal 16 of SDG, the study investigates sustainability communication in the tweets of Indian political leaders using word frequency and topic priority. Also, it is important to analyse polarity of tweets to understand hidden subjective interpretation. For this, sentiment analysis is performed using state-of-the-art BERTweet trained under roBERTa on Python. Abiding the principles of textual analysis in sentiment study and by deriving quantitative findings, the present study explains tweeting trends and SDG priority in tweets of ruling and opposition political party leaders in India.

Research Objectives

1) To analyze tweets of Indian political leaders in a politically vulnerable period
2) To analyze social indicators like peace, harmony, and inclusivity in the tweets of Indian political leaders.

Research Design

Data collection

For the study, Twitter's Application Programming Interface (API) was used to collect primary data as it enables crawling of tweets and extraction of user data. Popular Twitter API for Python, *Tweepy* was used for data collection. Top eight followed Indian political leaders on Twitter were selected, and their every tweet in the data collection period was extracted. Since the present study engaged in analysing only English language tweets, data of two selected political leaders namely Yogi Adityanath and Akhilesh Yadav couldn't be studied. Their Twitter handles engaged in Hindi language tweets. Thus, the top six followed Indian political leaders selected for the study are Narendra Modi (80.2 M followers), Amit Shah (29.8 M followers), Arvind Kejriwal (25.6 M followers), Rahul Gandhi (20.9 M followers), Smriti Irani (12.5 M followers) and Shashi Tharoor (8.3 M followers). Data collection period was between 8 June and 8 July, 2022. Tweets were stored in JSON file and then converted into CSV file on Python for better reading.

Sentiment analysis

For the present study, sentiment analysis is performed on the primary data (tweets). Sentiment analysis is to unearth those hidden judgments in a written/printed text and to understand the presence of emotions in them. It is also called opinion mining that provide information on polarity and context of tweets (Rill et al., 2014; Marco & Enrico, 2018). Sentiment analysis mines emotions, attitudes and viewpoints from speech, tweets, text, and

sources of databases. In the present study, tweets are classified into positive, neutral, and negative sentiment polarities. After the raw data is collected, they are pre-processed for analysis.

Pre-processing of data

Pre-processing is an important part of Twitter analysis. The raw data retrieved from Twitter contain redundant information, opinions and noise. Thus, to facilitate data analysis, unnecessary information had to be eliminated. Pre-processing includes removing blank spaces, abbreviation, punctuation marks, stop words etc. For the study, every tweet was broken into words. This technique is called *tokenization* where a block of text is broken into smaller fragments called tokens. During polarity detection in tweets, many words do not contribute to analysis like 'and', 'to', 'from' etc. These words are called stop-words and were cleaned for efficient sentiment analysis and higher accuracy. It should be noted that higher accuracy rates are possible only when raw data is processed well.

Thereafter, 732 uncompressed dataset was pre-trained. Every dataset consisted of at least 15- and 50-word tokens. Then, only the English language tweets were filtered. After the process of tokenization using 'TweetTokenizer' (Bird et al., 2009) from NLTK toolkit, emoji package was applied to convert all emojis into strings of text. Tweets were normalised by converting @-mentions and URLs into special tokens HTTPURL and @USER, respectively. All the tweets were filtered in terms of removing retweets, duplicates, and tweets with less 15 words. Thus, the final sample size for the study was 504 tweets. After this, sentiment analysis on BERTweet was performed.

BERTweet for sentiment analysis

BERTweet, a large-scale public pre-trained language model is used to perform sentiment analysis. BERTweet is trained under roBERTa (Liu et al., 2019) and fine-tuned by TweetEval. roBERTa (Robustly Optimised BERT Pretraining Approach) model is efficient

for English language tweets. It works on BERT's language veiling strategy. The system is trained to predict hidden text from unannotated data when implemented on Hugging Face Pipeline. BERTweet is known for its outperformance and higher accuracy. In this study, the model has delivered results with 0.9918 accuracy.

Coding includes:

```
from transformers import pipeline
sentiment_task = pipeline ("sentiment-analysis", model=model_path, tokenizer = model_path)
sentiment_task ("BJP's priority is all-round development of Telangana")
Output: [{'label' : 'Positive', 'score' : 0.7435}]
```

Analysis and Results

Social media has changed the dynamics of political communication. Political leaders post messages online and get public reaction within a few seconds. If the communication tool is popular, public reaction is rapid and expressed in forms like retweets, share, comment, hashtag and moments functions. Significant issues like SDG can be best propagated if tweeting on it is consistent and engaging in all seasons. In this regard, clarifying the *first research objective* to understand tweets of political leaders in a vulnerable period, findings show that week 4 has the highest tweet output with 33.2% and week 3 has the lowest output of 18.53%. Weeks 1 and 2 have an average output indicating that political actors are involved on Twitter in week 4 more than the other three weeks. While analyzing tweet content, it was observed that week 4 engaged in issues like presidential nomination for Draupadi Murmu, nomination of PT Usha in Rajya Sabha, bypoll results in Punjab, Andhra Pradesh, Jharkhand and Delhi. Weeks 3 and 4 also addressed celebrations such as Doctors' Day, CA Day, digital India week in Gandhinagar, G7 Summit, inauguration of Vanijya Bhavan and Udyami Bharat working towards trade, commerce and MSME in India. Tweets on these issues involved higher user generated content.

Table 1 shows that out of top six followed Indian political leaders, three are from BJP. Also, Narendra Modi is the most popular Indian politician on Twitter with 80.2 M followers. As per the above data, Narendra Modi has the highest twitter engagement with 179 tweets as compared to other popular political leaders. This is followed by Shashi Tharoor from INC with 157 tweets, then Smriti Irani and Amit Shah from BJP again with 69 and 44 tweets respectively. Finally, Arvind Kejriwal from AAP has 24 tweets during the data collection period. It should be noted that tweets from incumbent political party is more than opposition party. Creating an echo chamber structure through tweets from the same political party, users become vulnerable to party inclination (Colleoni et al., 2014). These rigid structures echo same ideologies and opinions making exposure towards any opposition view extremely challenging.

Table 1: Total number of tweets by political leaders

Political Leader	**Political Party**	**Number of tweets**
Narendra Modi	BJP	179
Shashi Tharoor	INC	157
Smriti Irani	BJP	69
Amit Shah	BJP	44
Rahul Gandhi	INC	31
Arvind Kejriwal	AAP	24
Total	**504**	

Apart from frequency of tweets, it is also critical to understand the tone in tweet content. For this, sentiment analysis was performed where text polarity wasanalysed. **Table 2** shows sentiment polarity as positive, neutral, and negative. Percentage of positive tweets is highest, followed by neutral tweets and then negative tweets. Narendra Modi has the highest percentage of positive tweets, while Shashi Tharoor has the highest percentage of neutral

and negative tweets. This trend indicates that in the Twitter echo chamber, exposure to positive tweets is from BJP, and exposure to neutral or negative tweets is from the opposition parties. If we further analyze sentiment of other BJP leaders in **Table 2**, percentage of positive and neutral sentiments is higher compared to negative sentiment. While opposition party leaders (INC and AAP) show higher percentage of negative sentiment over positive and neutral. Such similarity index among the leaders within same political parties' garner voter reciprocity and ideological support (Perl et al., 2015). **Table 3** shows a sample of polarity classification in processed tweets along with accuracy scores in Bertweet and roBERTa

Table 2: Sentiment polarity in tweets (In percentage)

Political Leader	**Positive (%)**	**Neutral (%)**	**Negative (%)**
Narendra Modi	55.63	30.6	5.26
Shashi Tharoor	20.86	37.31	63.16
Smriti Irani	13.58	11.19	7.02
Amit Shah	6.29	11.94	1.75
Rahul Gandhi	1.99	3.73	21.05
Arvind Kejriwal	1.66	5.22	1.75

Table 3: Examples of polarity classification

Processed Tweet	Bertweet	Bertweet Score	Roberta	Roberta Score
exposing bjp hate bigotry lies threat arresting voice truth always triumphs over tyranny	Negative	0.95	Negative	0.87
transformative initiatives development northeast	Positive	0.96	Positive	0.91
mha national investigation agency investigation brutal murder kanhaiyalalteli committed Udaipur rajasthan yesterday involvement organization international links investigated	Neutral	0.97	Neutral	0.78

Following this, answering the *second research objective* to understand sustainability communication in the tweets of top followed Indian political leaders word cloud analysis was performed. Word count in a text by a political leader emphasizes its significance. **Figure 1** shows word cloud analysis - a visual representation of word frequency. Higher the word appears; more is the chance for it to be included in the word cloud. From the entire corpus in the study, 44 terms were repeated and included in word cloud analysis. The eight most frequently appeared words were - *elections, BJP, polarization, politics, Udaipur, inflation, yoga, and floods*. It can be observed that four out of eight terms are related to politics conforming tweeting focus on elections and its indicators like politics, BJP, polarization. Other supportive terms related to politics were 'polls', 'vendetta' and 'vote' showing importance of elections even in a communally vulnerable period. In addition, opposition parties have counter reacted winning in elections with words such as 'vendetta', 'polarization' and 'politics'.

The other three out of eight repeated words were 'Udaipur', 'floods', and 'inflation'. But they failed to materialize a strong sustainability Twitter conversation due to lack of other supportive sustainability terms, user engagement in forms of retweet, hashtags, or use of digital affordance, and lower in political priority. This trend came as a surprise owing to the communal tragedy in Udaipur and its consequential killings. Terms like 'horror', 'support', and 'community' made a minor appearance. Towards floods in Assam, landslide in Manipur and earthquake in Afghanistan, terms like 'rainfall', 'rescue', 'grassroot' and 'marginalized' appeared with a minimal frequency ignoring marginalized communities during crisis. However, 'Yoga' was a frequent word promoting healthy lifestyle as 21stof June was International Yoga Day. Words like 'sustainability', 'SDG-2030', 'United Nations', 'Agenda-2030', 'peace', 'harmony', and 'inclusivity' were not mentioned in the tweets of selected Indian political leaders during data collection period.

Thus, word cloud analysis has reflected a minimal representation of SDG-2030 in the tweets of the most followed Indian political leaders. Despite vulnerability in socio-political situation during the data collection period with communal killings and natural disasters, primary focus of political leaders was on election results and party promotions. Goal 16 of SDG states that sustainable development is possible only in peaceful societies that showcase peace, harmony, strong judicial system, legal identity, and inclusive institutions. Since political leaders act as influencers to the masses, their lack of communication on SDGs on popular social media platforms will pose a serious threat to sustainable living for years to come. Communication campaigns and awareness should be adopted for sustainable practices (**Grover et al., 2021**)

Figure 1: Word Cloud Analysis of the tweet content

Conclusion

This study has attempted to understand tweeting behaviour of top followed Indian political leaders and their interest in promoting SDGs. While the digital audience penetration is dominated by Facebook, Instagram, and Pinterest, Twitter stands fourth in popularity followed by LinkedIn. But, Twitter is considered a serious social networking site in terms of exchanging '*textual*' information to the public unlike Facebook that involves '*social interaction*' among friends and family, and Instagram or Pinterest that emphasize *'photo and video sharing'* (Forsey, 2021). Twitter interface provides a maximum of 280 characters for short text messages that can be written and read by any other Twitter user. Third-party tools to analyze tweets can be employed efficiently, and if the data is small, APIs allow for free retrieval of Twitter data as compared to other social networking sites.

The study has emphasised on understanding SDG taxonomies like inclusive society, peace and harmony in the backdrop of socio-political vulnerability of the data-collection period. It is understood that political leaders act as influential agents in promoting any issue of significance. Similarly, social networking sites help in rapid and convenient dissemination of information. Research findings have shown minimal indulgence in spreading 'non-

violence' tweets by Indian political leaders even in a communally disturbing period. Jabbour et al. (2019a) has mentioned that political leaders, policymakers, academia, governments and society should work in collaboration, this study also emphasises the same considering the criticality of SDG – 2030.

The findings have also witnessed positive tweets from the ruling party leaders and negative or neutral polarity tweets from the opposition party leaders. This suggests the presence of echo chambers within Twitter. Being a powerful communication tool such echo chambers promote political orientation and mobilise people towards political ideologies (Colleoni et al., 2014).

While aiming to understand involvement of top political leaders from different parties in critical times like floods in Assam, landslide in Manipur and earthquake in Afghanistan, it was surprising to observe that words like 'rainfall', 'disaster', 'grassroots', 'marginalised', 'development', 'SDG', 'India', 'support' did not make frequent appearance in word cloud analysis. Hence, it is evident that tweeting priorities of Indian political leaders are elections and party promotions. This study strongly emphasises on rekindling and redirecting online interactions towards promoting SDGs. As evident, communication is not a challenge in the presence of social networking sites. As (Hawn, 2009) states that Twitter is a powerful communication tool, integrating political priorities with SDGs can serve as an ideal communication strategy towards Agenda – 2030 for India. The findings have practical and scholarly implications.

Implications of the study

Findings of the present study can be meaningfully utilised by policymakers, political leaders, NGOs and decision making authorities to increase awareness on SDGs among the masses. Criticality of Agenda - 2030 can be best understood from a local point of view and a goal specific implementation involving native issues. NITI Aayog report stated that no

sustainable development can take place without a peaceful society that is in isolation from violence and fear. Thus, a collective action from government, industry, and public, aiming towards sustainable lives and thinking tendencies of marginalized can demonstrate an effective implementation of SDG. In addition, country-specific goals targeting local issues can lead to deeper penetration of urgency in implementing SDGs. Also, natural disasters like floods, landslide, earthquake, draught etc... have become prominent owing to climate change and environmental degradation. There is immense literature on climate change repercussions, and the results of this study can be utilised to formulate far-reaching communication mechanisms for Indian political leaders to use Twitter for promoting SDGs. Once the progress begins, strategies can be defined for non-government decision making authorities and influential celebrities. From methodological point of view, this study recommends using computational research methods for rapid, operative and timely analysis against manual content analysis. As mentioned, for the present study, use of emerging technologies such as BERTweet trained under roBERTa has produced highest accuracy. This method can be adopted by the academia for future studies.

References

Ali, M., Azab, N., Sorour, M.K., & Dora, M, (2019). Integration v. polarization among social media users: Perspectives through social capital theory on the recent Egyptian political landscape. *Technological Forecasting and Social Changes*, 145, 461-473. https://doi.org/10.1016/j.techfore.2019.01.001

Allen, C., Metternicht, G., &Wiedmann, T. (2017a). An iterative framework for national scenario modeling for the Sustainable Development Goals (SDGs). *Sustainable Development,* 25 (5), 372-385. https://doi.org/10.1002/sd.1662

Bird, S., Klein, E., &Loper, E. (2009). Natural language processing with Python. O' Reily Media, Inc. http://www.nltk.org

Colleoni, E., Rozza, A., Arvidsson, A. Echo chamber or Public Sphere? Predicting political orientation and measuring political homophily in Twitter using big data. *Journal of Communication*, 64 (2), 317-322. https://doi.org/10.1111/jcom.12084

Dahlgren, P. (2006). The Internet, Public Spheres, and Political Communication Dispersion and Deliberation. *Political Communication*, 22 (2), 147-162. https://doi.org/10.1080/10584600590933160

Devlin, J., Chang, M.W., Lee, K., & Toutanova, K. (2019). *BERT: Pre-training of deep Bidirectional Transformers for Language Understandin*g. In proceedings of the 2019 conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 1, 4171-4186. https://doi.org/10.18653/v1/N19-1423

Forsey, C. (2021, July 26). Twitter, Facebook, or Instagram? Which Platform (s) You Should Be On. https://blog.hubspot.com/marketing/twitter-vs-facebook

Grover, P., Kar, A.K., Gupta, S., & Modgil, S. (2021). Influence of political leaders on sustainable development goals – insights from twitter. *Journal of Enterprise Information Management*, 34 (6), 1893-1916. https://doi.org/10.1108/JEIM-07-2020-0304

Hawn, C. (2009). Take two aspirin and tweet me in the morning: How Twitter, Facebook and other social media are reshaping health care. Health Affairs, 28 (2). https://doi.org/10.1377/hlthaff.28.2.361

Jabbour., C.J.C., Sarkis, J., de Sousa Jabbour, A.B.L., Renwick, D.W.S., Singh,S.K., Grebinevych, O., Kruglianskas, I., &Godinho, M. (2019b). Who is in charge? A review and a research agenda on the "human side" of the circular economy. *Journal of Cleaner Production*, 222(10), 793-801. https://doi.org/10.1016/j.jclepro.2019.03.038

Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., &Stoyanov, V. (2019). *Roberta: A robustly optimized bert pretraining approach.*

Marco, C., & Enrico, G.C. (2018). Revealing political sentiment with Twitter: The case study of the 2016 Italian Constitutional Referendum. *Proceedings of IEEE/ACM International Conference on advances in social networks analysis and mining* (ASONAM), 861-868. https://doi.org/10.1109/ASONAM.2018.8508243

Perl, J., Wagner, C., Kunegis, J., &Staab, S. (2015). Twitter as a Political Network: Predicting the following and unfollowing behaviour of German politicians. *Proceedings of the ACM Web Science Conference*, 51:1-2. https://doi.org/10.1145/2786451.2786506

Plummer, M., Palomino, M.A., Masala, G.L. (2017). Analysing the sentiment expressed by political audiences on Twitter: The case of the 2017 2017 UK General election. *Conference proceedings of the 2017 International Conference on Computational Intelligence (CSCI),* 1449-1454. https://doi.org/10.1109/CSCI.2017.253.

Ramesh, A. (2022). Algorithmic Analysis of Political Tweets: A Systematic Literature Review. *SRELS Journal of Information Management*, 59 (4), 185-195. https://doi.org/10.17821/srels/2022/v59I4/170345

Reyes-Menendez, A., Saura, J.R., Alvarez-Alonso, C. (2018). Understanding #WorldEnvironmentDay User Opinions in Twitter: A topic-based sentiment analysis approach. *International Journal of Environmental Research and Public Health,* 15 (11), 25-37. https://doi.org/10.3390/ijerph15112537

Rill, s., Reinel, D., Scheidt, J., &Zicari, R.V. (2014). PoliTwi: Early detection of emerging political topics on twitter and the impact on concept-level sentiment analysis. *Knowledge Based Systems*, 69, 24-33. https://doi.org/10.1016/i.knosys.2014.05.008

Schramade, W. (2017). Investing in the UN sustainable development goals: Opportunities for companies and investors. *Journal of Applied Corporate Finance*, 29 (2), 87-99. https://doi.org/10.1111/jacf.12236

Sciandra, A., Surian, A., &Finos, L. (2021). Supervised Machine Learning Methods to disclose action and information in "U.N. 2030 Agenda" Social Media Data. Social Indicators Research, 156, 689-699. https://doi.org/10.1007/s11205-020-02523-4

Sedera, D., Lokuge, S., Atapattu, M., &Gretzel, U. (2017). Likes – the key to my happiness: The moderating effect of social influence on travel experience. *Information and Management,* 54(6), 825-836. https://doi.org/10.1016/j.im.2017.04.003

Singh, A.K., Gupta, D.K., & Singh, R.M. (2017). Sentiment Analysis of Twitter User Data on Punjab Legislative Assembly Election, 2017. *I.J. Modern Education and Computer Science*, 9, 60-68. https://doi.org/10.5815/ijmecs.2017.09.07

Vakeel, K.A., &Panigrahi, P.K. (2018). Social media usage in E-Government: mediating role of government participation. *Journal of Global Information Management*, 26 (1), 1-19. https://doi.org/10.4018/JGIM.2018010101

Wu., J., Guo, S., Huang, H., Liu, W., & Xiang, Y. (2018). Information and communication technologies for sustainable development goals: state-of-the-art, needs and perspectives. IEEE Communications Surveys and Tutorials, 20 (3), 2389-2406. https://doi.org/10.1109/COMST.2018.2812301