UNDERSTANDING THE VOICE AND EMOTIONs OF THE CITIZENS OF BRICS NATIONS ON OUTCOME BASED EDUCATION

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doi: 10.48047/ecb/2023.12.si4.1172

Abstract: BRICS is a group of five emerging economies that include Brazil, Russia, India, China, and South Africa. These nations have a combined population of over 3.6 billion people, accounting for approximately 42% of the world's population. As emerging economies, these nations face various challenges related to poverty, inequality, and environmental degradation. The Sustainable Development Goals (SDGs) provide a framework for addressing these challenges and achieving sustainable development. This article highlights the 4th SDGs, named outcome-based education (OBE) practices in BRICS nations for quality education.

In the current scenario, Google trends analysis and Twitter both platforms are famous for listening to the voice of the citizen of a person/ a group, or a nation. Understanding the public opinions and sentiments expressed through tweets can greatly help worldwide political and commercial use.

Further, this research article has done the Google trends analysis and extracted tweets for sentiment analysis for OBE practices in BRICS nations. R and its associated packages are used to display word clouds and bar diagrams to depict the subjectivity and polarity (mood) of the public of BRICS nations about the OBE. This research work can help the government of BRICS counties to formulate outcome-based education policies to manage the opinions and emotions of the people for the prosperity of their respective countries. This research can attract and motivate other researchers to work in this direction.

1. Introduction:

We are currently in the era of the internet, commonly referred to as the internet age, which has revolutionized how people express their opinions and views through various online platforms such as social media, product review websites, online forums, and blog posts. Google search engine and Google trend analysis is very helpful tool to know where is my customer and what is their voice. Other hand social media networking sites, including Twitter, Facebook, Instagram, and Google Plus, have become a popular means for millions of people to share their emotions, views, and opinions. Twitter, which was created by Jack Dorsey, Noah Glass, and Evan Williams in March 2006, gained worldwide popularity and was among the top ten most-visited websites in 2013. As of 2018, Twitter has an average of 336 million monthly active users and generates a large volume of sentiment-rich data in the form of tweets, blog posts, comments, and likes due to the increasing interaction among individuals on the internet.

Twitter is an ideal social networking forum for people to express their views quickly and easily, making it a rich source for public opinion and sentiment analysis. Given that tweets are limited to 140 characters, the emotions or feelings of Twitter users on specific topics remain consistent. Sentiment analysis is essential in determining the sentiment of each tweet, whether it is positive, negative, or neutral. Government agencies and multinational companies use these data to inform their policy decisions and improve their offerings. Similarly, social media users can connect with businesses, and companies can gain insights into their customers. Customers can also check product reviews from specific brands, which has prompted companies to use sentiment analysis techniques to understand their customers' mindsets.

The process of sentiment analysis involves using Natural Language Processing (NLP) (Kharde and Sonawane, 2016) to convert attitudes, views, opinions, and emotions expressed in text, tweets, and other database sources into distinct categories, namely positive, negative, and neutral. This process is also referred to as subjective analysis, appraisal extraction, and opinion mining. The vast and unstructured data generated through social media websites contains valuable information that can be utilized by government agencies and companies for future planning.

The BRICS countries, which include Brazil, Russia, India, China, and South Africa, collectively own 1/3 of the world's farmland and have a population that covers 40% of the globe. Given their significant agricultural production, these countries play a critical role in ensuring global food security and have made agriculture a top priority on their respective government agendas. Since March 2010, the BRICS countries have held annual meetings of their Ministers of Agriculture and Agrarian Development, creating a long-term mechanism for agricultural cooperation and exchanges. The most recent meeting, the 7th of its kind, focused on agrarian development and emphasized the need for innovation to meet the international goal of eradicating hunger and poverty.

In this study, we collected and analyzed data from Twitter related to agriculture from the five BRICS countries. These countries are similar in many ways, being developing economies with vast regions and large populations. We focused on analyzing the sentiment of recent tweets on agriculture in these countries, using the most recent 1000 tweets from each. The rest of the paper is organized as follows: related work and research gaps are discussed in Section 2, the methodology and research design are detailed in Section 3, the results and discussion are presented in Section 4, and conclusions are drawn in Section 5.

2. Literature review:

Sentiment analysis has been approached as a Natural Language Processing task at various levels of detail. Initially, it was treated as a classification task at the document level (Turney, 2002), (Pang and Lee, 2004), and later it was also conducted at the sentence level (Hu and Liu, 2004), (Kim and Hovy, 2004), and even at the phrase level more recently (Wilson et al., 2005), (Agarwal et al., 2009). A comprehensive overview of the previous studies on opinion mining and sentiment analysis was presented by (Pang and Lee, 2008). The techniques and approaches for opinion-oriented information retrieval were also explained in addition to presenting the algorithms for sentiment detection. One such simple algorithm, called semantic orientation, was introduced by (Turney, 2002). Meanwhile, (Pang and Lee, 2004) proposed a hierarchical classification scheme in which text is initially classified as having sentiment and then categorized as either positive or negative.

Numerous papers have been dedicated to sentiment analysis in the areas of blogs and product reviews. Researchers like Jansen have analyzed the impact of micro-blogging on brands. Several studies on sentiment analysis of Twitter data have been conducted, including early and recent ones by Go et al. (2009), Barbosa and Feng (2010), Bermingham and Smeaton (2010), and Gamon (2004), who performed sentiment analysis on feedback data from Global Support Services survey. Pak and Paroubek (2010) suggested a model to classify tweets into objective, positive, and negative categories, creating a Twitter corpus using Twitter API and annotating tweets using emoticons. Davidov et al. (2010) proposed a method of using user-defined hashtags in tweets to classify sentiment type using punctuation, single words, n-grams, and patterns as different feature types that are combined into a single feature vector for sentiment classification. In recent years, many papers have examined Twitter sentiment and buzz, including those by O'Connor et al. (2010), Tumasjan et al. (2010), Bifet and Frank (2010), Barbosa and Feng (2010), and Davidov et al. (2010). Po-Wei Liang et al. (2014) used Twitter data in three categories (camera, movie, mobile) and labeled the data as positive, negative, and non-opinions. Although Davidov et al. (2010) used hashtags to create training data, their experiments were limited to sentiment/non-sentiment classification rather than 3-way polarity classification.

According to (Klein and Manning, 2003), the field of text classification using machine learning has been extensively researched. (Go and Hyung, 2009) and (Pang and Lee, 2002) explored the effects of various machine learning techniques such as Naive Bayes (NB), Maximum Entropy (ME), and Support Vector Machines (SVM). In a similar vein, (Parikh and Movassate, 2009) employed both Naïve Bayes and Maximum Entropy models for classifying tweets. (Fellbaum, 1998) edited WordNet, an electronic lexical database that is widely regarded as the most critical resource for researchers in computational linguistics and text analysis. Additionally, (Whissel 1989) investigated the Dictionary of Affect in Language, which is one of the several acceptable methods for measuring emotion, both in terms of the research carried out with the dictionary and in terms of a meta-measurement framework. (Haussler, 1999) introduced a method for constructing kernels on sets containing discrete structures such as strings, trees, and graphs. The approach can be implemented iteratively to create a kernel on an infinite set using kernels that involve the set's generators. (Klein and Manning, 2003) demonstrated that unlexicalized probabilistic context-free grammars (PCFGs) can achieve high parsing accuracies when training trees are annotated with additional information. Finally, (Moschitti A., 2006) conducted a study on the use of tree kernels to encode syntactic parsing information in natural language learning.

3. Gap Analysis:

The literature on sentiment analysis of Twitter data and news articles has primarily focused on the methodology and analysis of data related to specific topics such as cameras, movies, and mobile devices. However, the outcome-based education sector plays a critical role in equipping individuals with valuable skill sets, driving global economic growth, and providing better living opportunities to overcome poverty. Given that education is a crucial industry for densely populated countries like the BRICS nations, which represent 41% of the world's population and hold significant regional influence, it is surprising that there is a lack of research on analyzing and understanding public sentiments towards this important issue. Therefore, there is a significant gap in the literature on sentiment analysis in the context of outcome-based education.

4. Problem Formulation:

After reviewing the literature and identifying a gap in research, it was found that no previous study has focused on sentiment analysis of BRICS countries' attitudes towards outcome-based education. This gap in knowledge serves as motivation for the current study. The primary goal of this research is to gain insight into the opinions and emotions of the people in BRICS countries regarding outcome-based education. By employing tools such as Twitter sentiment analysis and Google trend analysis, this research aims to provide valuable information to the respective governments of BRICS countries to formulate outcome-based education policies for their stakeholders and promote the prosperity of their nation. However, to conduct sentiment analysis on BRICS countries' attitudes towards outcome-based education, a dataset is required. Thus, to collect and analyze the necessary data, a flowchart will be utilized. The objective of this research article are

- To know the research practices on “Outcome-based education” research in BRICS nations
- Which BRICS nation is doing better in OBE?

5. Data Collection:

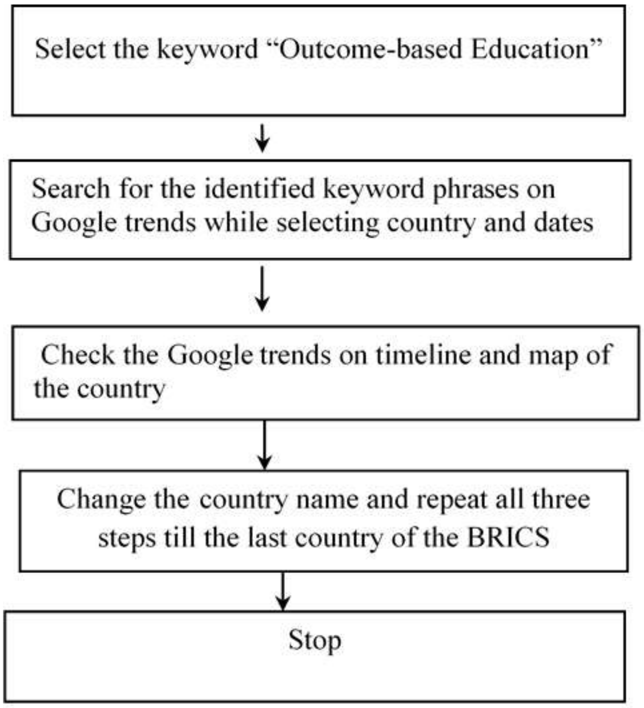

Figure. 1 (a) Flow chart of Google trends Analysis for OBE

Figure. 1(b) Flow chart of the steps for sentiment

Figure. 1 (a) presents a proposed flow chart for conducting Google trends analysis, step by step for all five nations of BRICS starting from Brazil to South Africa. Whereas as per Figure. 1 (b) presents a proposed flow chart for conducting sentiment analysis, which involves five distinct steps. These steps include extracting tweets, cleaning the data, converting the cleaned data into term-document format, generating visualizations such as barplots, and word clouds, and finally performing sentiment analysis. The first step entails gathering raw data from tweets, while the second step involves removing any unnecessary information from the collected data. The third step involves converting the cleaned data into a term-document format, which can then be used for various visualization techniques in step four. The fifth and final step involves conducting sentiment analysis on the processed data.

6. Data Analysis and Results Discussion

6a) Google trend analysis for BRICS nations:

Figure 2(a) depicts there Outcome based education (OBE) has become a hot topic world-wide. In first view of Figure 2(a) among the BRICS nations only India and South Africa is showing some response w.r.t. outcome based education query in Google-trends.

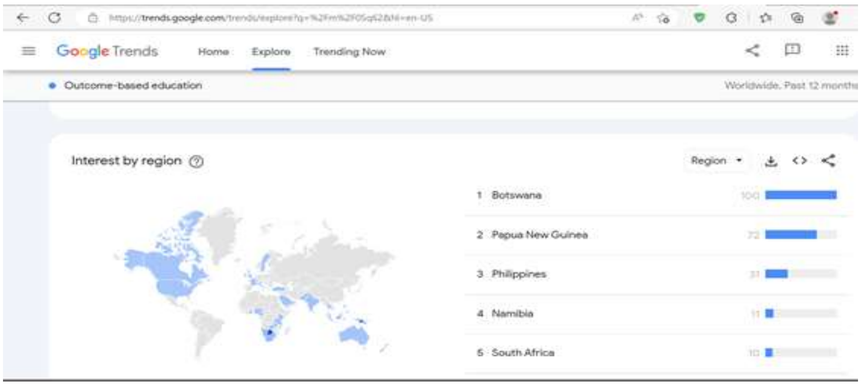

Figure. 2 (a) Google trends Analysis for OBE at world level

Figure. 2 (b) and Figure. 2 (c) represent that there is no query is raised in Google for OBE.

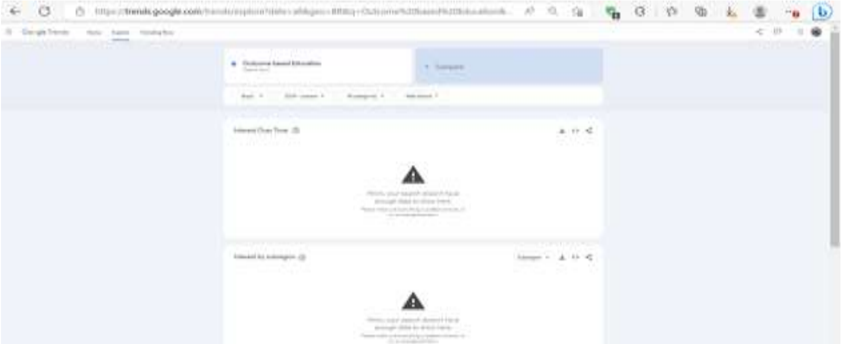

Figure. 2 (b) Google trends Analysis for OBE for Brazil

Figure. 2 (b) depicts that citizen of Brazil may be not raising their voice on "Outcome-based education" right now as per the Google trends.

Figure. 2 (C) Google trends Analysis for OBE for Russia

On same fashion of Brazil the citizens of Russia may be not raising their voice on "Outcome-based education" right now as per the Google trends as mentioned in Figure. 2 (C)

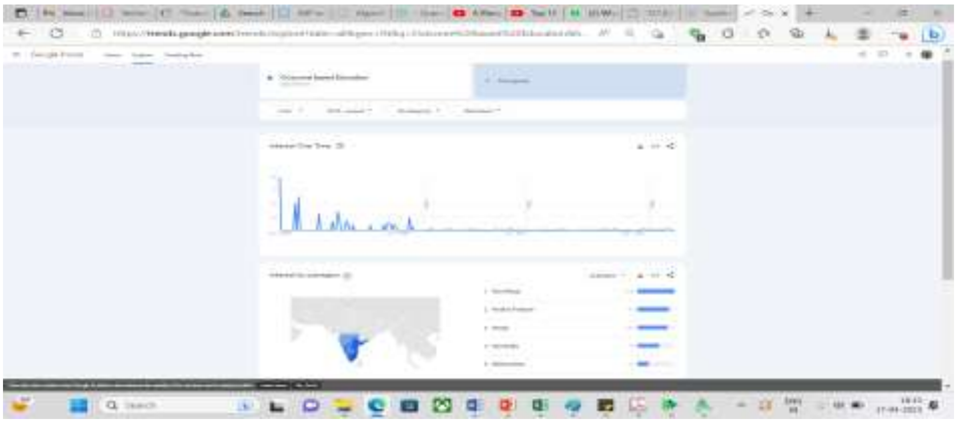

Figure. 2 (d) Google trends Analysis for OBE for India

As per Figure. 2 (d), there is good voice for “Outcome-based education” in India especially in southern part of India. You may also conclude that citizen of India are well aware of “Outcome-based education” as per the Google trends.

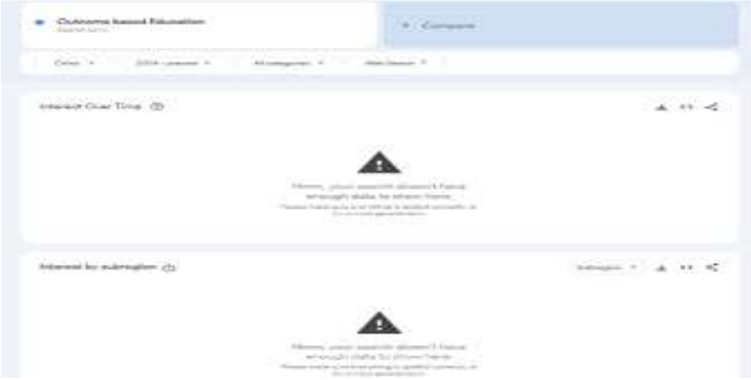

Figure. 2 (e) Google trends Analysis for OBE for China

As per the Figure. 2 (e) citizens of China may be not raising their voice on “Outcome-based education” right now as per the Google trends. Moreover Google is banned in China. China is using Baidu as a search engine.

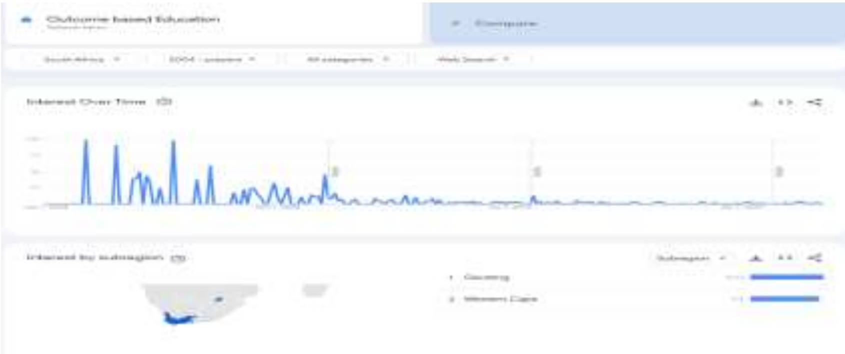

Figure. 2 (f) Google trends Analysis for OBE for South Africa

Figure. 2 (f) depicts that citizen of South Africa are also raising their voice on “Outcome-based education” as per the Google trends.

6b) Voice and view through Twitter of BRICS Nations: In this section we try to capture the voice of the citizen of BRIC nations by using Twitter. When we try to extract the tweets for BRICS nations only a good number of tweets extracted in case of India. Based upon extracted tweets we have constructed the word cloud to know the subjectivity on the OBE and Twitter sentiment analysis to know the polarity of the people on OBE. Figure. 2 (g) is about the Word cloud for OBE for India from tweets, whereas Figure. 2 (h) depicts the sentiments of the people of India on OBE, which is more positive as compare to negative, more trust as compare tp surprise, more joyful as compare to sadness. In year 2021 India has introduce its new education policy (NEP) which is advocating the OBE.

Figure. 2 (g) Word cloud for OBE for India from tweets

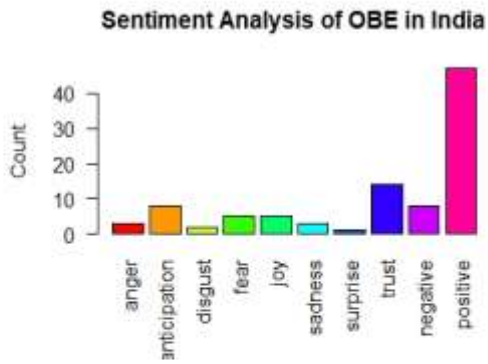

Figure. 2 (h) Sentiment Analysis for OBE in India

There are few factors affecting the adoption of OBE in BRICS nations viz. Policy and regulatory frameworks, Faculty development and training, Assessment methods and tools, Infrastructure and resources; and Societal and cultural factors

7. Limitation and Future scope

- Limitation of this study is that, data sources are restricted to Google trends and Twitter only. Also, this research focused on OBE only. Researcher can use the other data sources like Scopus, Baidu (Chinese SE), Yandex (Russian SE) data used.
- Researcher can also make many other combinations of OBE and objectives of OBE.
- Empirical research is also one of main area where researchers can work to know the factors affecting the OBE in BRICS nations or any other one.

Conclusion

This research paper highlights the importance of Google Trends and Twitter sentiment analysis of BRICS countries about the outcome based education. As per Google trend analysis the citizen of India and South Africa are more curious and raising their voice on OBE, rest BRICS countries may not be talking about OBE. According to Twitter Analysis, only Indian are raising their voice on Twitter among the BRICS nations. As per the visualizations of the most frequent words containing #eduaction keyword the form of wordclouds indicated that the most frequent key word for India is ‘education’ followed by ‘Outcome”. Other hand sentiments of the people of India on OBE, which is more positive as compare to negative, more trust as compare to surprise, more joyful as compare to sadness.

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