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What Indians are Talking About LIS Research on X: An Altmetric Analysis Through Opinion Mining and Sentiment Analysis

Vysakh. C

Department of Library and Information Science, Kannur University, Kerala – 670 002, India
Email:chingathvysakh@gmail.com

ABSTRACT

The present study aims to measure user sentiments while conversing about Library and Information Science (LIS) research on X; previously, Twitter ('X' and 'Twitter' are used interchangeably throughout the paper). The study also aimed to estimate the webometric and altmetric features of the LIS scholarly outputs regarding citations, altmetric scores, and Twitter metrics. Altmetric.com served as the primary source of data collection. Using an instant data scraper, the tweets and retweets were extracted and subjected to sentiment analysis in Orange text mining software. The study revealed 102,221 LIS outputs were indexed in the Altmetric Explorer, and 62995 outputs had social web attention. Twitter mentions were more prevalent for recent LIS publications. Geographically, 237 countries globally discussed LIS research on the X platform. The highest mentions came from English-speaking countries, such as the United States of America (USA) and the United Kingdom (UK), with 87,969 and 44,356 mentions, respectively. As far as India was concerned, only 1925 LIS articles were mentioned. The sentiment analysis discovered that most of the Tweets were neutral. The study proved that early tweets can predict later citations for LIS research. The study's findings give insights to the scholarly community on the scientific progress of the LIS domain by assessing public opinion on the X platform.

Keywords: Altmetrics; Sentiment analysis; Twitter; Tweets; Text mining; Opinion mining

1. INTRODUCTION

Recently, there has been rapid growth in the consumption of social media platforms like blogs, Facebook, Google+, and Twitter, where users can express their thoughts and opinions publicly on any topic[1]. The unstructured data produced during the web-based activities in the form of online reviews, comments, opinions, and posts has accounted for 80 % of the total information[2]. The need to assess the sentiment of web conversations led to the evolution of a broad domain called opinion mining or text mining[3].

Sentiment analysis has become a hot area for research in the scientific community and is treated as a part of opinion mining[4]. Companies, political parties, government organisations, educational institutions, etc., carry out emotional analysis to make valuable decisions by determining the nature of the text available on the web about their product, events, or entities[5]. The sentiments are generally treated as negative, positive, or neutral[6-7.] Since social media platforms offer large unstructured data sets, Opinion Mining and Sentiment Analysis (OMSA) have become key research areas for researchers[8-9].

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X is a well-known social networking site that lets users engage in public discussions, share breaking news, and access information from various sources[10]. Data miners rely upon X platforms for opinion mining since they offer real-time public data for sentiment analysis[11]. The use of X platforms among the research community for promotional purposes of their research outputs has been apparent[12]. A previous study reported that 1 to 5 % of Twitter users are active scientists[13]. They post their published research and converse with their peers and experts through networks developed through this microblogging platform[12]. The metrics, i.e., tweets and retweets to these research outputs, have become a key indicator for calculating the social impact of the articles and have been named alternative metrics or altmetrics[14] The discussion that authors usually have regarding the research and research outputs on Twitter has been used for OMSA[15].

It was learned that the scholarly community had not made previous efforts to study what the Indian academic community talks about LIS research or research in other major domains on social media platforms. Assessing what users expressed about the library, its services, collections, etc. on social media platforms has already been done by many scholars across the world[16,17,18,19]. However, nothing is known concerning the discussion of Library and Information Science (LIS) scholarly outputs on social media platforms. Scholarly communication through social platforms, especially Twitter, helps the community know about scientific progress in that domain[20]. Furthermore, early tweets can predict the future impact of the article in terms of citations[21]. Thus, a research gap exists, and the present study aims to bridge this gap.

2. PREVIOUS STUDIES

X generates large volumes of opinion texts in tweets and retweets, which can be subjected to sentiment analysis[22]. Several studies have been conducted using the OMSA techniques, including sentiment analysis of events[23-26], products[27-28&29], services[30-31-32-33&34], etc. This section critically presents previous studies on altmetrics and OMSA concerning research.

A sentimental analysis of Twitter discussion regarding a research article can reveal the interest in it and its impact[35]. Thelwall[36], *et al.* conducted a pilot study in 2012 by considering 270 tweets linking to articles in four journals to assess how articles are being tweeted. The study reported that tweets relating to articles were objective, involving the title of the articles or their summary. The researchers concluded that tweets give little insight into the researchers' responses to articles because of their low appreciation and lack of criticism.

Natalie Friedrich[37], *et al.* conducted a similar study assessing 487610 tweets about 192832 articles from various disciplines. Using Sentistrenth, they found a few positive and negative sentiments regarding the articles of X users. Most of the tweets were neutral. The discipline-wise sentiments revealed that the highest sentiment was from psychology, social science, and humanities, while physics, engineering, and chemistry recorded the least sentiments.

Okere and Onyebinama[38] assessed the conversation held on open access by tracking 64 tweets published between May 1 and 7, 2022. The Scholars and independent researchers were identified as the major users discussing open access. Moreover, most of the discussion was on article processing charges, paywalls, repositories, etc. 15 % of the posts were negative regarding paywalls, including the terms unaffordable, untenable, and oligopolistic.

Robinson-Garcia[39], *et al.* assessed the tweeting patterns of dental research articles by studying the 8206 tweets about 4358 dental papers from 2202 US-based Twitter handles for 5 years from June 2011 to June 2016. The study discovered that highly cited dental articles were not highly tweeted and vice versa. Contrary to this, Chan[40], *et al.* reported that tweets led to 16 to 25 % more citations to working papers of Economics published in VoxEU. The presence of bots in tweeting the articles was also deduced through this investigation. Additionally, they discovered that human tweets always start with '@' with an account name or are tagged by X as replies. Another observation by Boyd[41], *et al.* was that active Twitterati were less likely to retweet than those who engage on Twitter for conversations or to share information.

Wakeling[42], *et al.* assessed the Twitter activities of PLOS journals from 2003 to 2016 and showed that the overall commenting on articles was less, with variation in tweets across different titles. PLOS Medicine (22 %) and PLOS Biology (13 %) were the journals with the highest number of Twitter discussions, while PLOS Neglected Tropical Diseases (4.5 %) had the lowest number of comments. It was also revealed that 22.2 % of the PLOS Medicine articles had at least one comment. Besides, the study reported that journal size and the proportion of articles with comments had negative associations.

The current work aims to fill the gap revealed by examining previous research, which discovered that Twitter sentiment analysis of LIS research outputs has not been done.

3. OBJECTIVES OF THE STUDY

- To gauge the webometric and altmetric features of the LIS research outputs regarding citations and altmetric attention score.
- To assess the geographical distribution of tweets to LIS research outputs.
- To carry out sentiment analysis of conversations about LIS research on Twitter.
- To know whether early tweets can predict later citations for the LIS research outputs.

4. DATA EXTRACTION AND METHODOLOGY

The data collection for the present study was carried out in different phases. In the beginning phase, Altmetric Explorer, a service offered by Altmetric.com, was accessed. To find the relevant LIS literature, an advanced search in Explorer was executed by selecting the subject category "Library and Information Studies" with category number 4610 during the last week of December. From the total outputs tracked by the database (N=102221), 62995 outputs had attention from various social media platforms without setting other search refinements like type of outputs, open access, language, etc. Later, the "mentions" tab offered by Explorer was used to filter the mentions from X. There were two options, including "X posts (all)" and "X posts original". For the present study, the latter were chosen. Subsequently, India was selected in the country refinement tab, while the period of mentions was kept blank. The search and results displayed X posts from the latest to the oldest. 4938 articles were mentioned in 4903 individual posts. The result was downloaded as a CSV file, and later, the DOIs of these 4938 articles were copied and searched again in Altmetric Explorer. It was found that only 1925 outputs had social media attention. The geographical distribution of the articles was extracted by using the demographics option.

In the second phase, the Tweets and retweets were extracted using an instant data scraper, a free extension offered by Chrome. Each page and its respective comments were scraped, and the final results were downloaded as a CSV file for the ensuing analysis. The scraping took 86 seconds to finish. The downloaded CSV files included different details, including the Twitter handles, abstract of the comments, time of comments, link to altmetric page, badge, journal details, etc. There were duplicate tweets removed using the conditional formatting option in Excel. There were 357 tweets in total. The individual tweets were saved in a separate Excel file as CSV for the OMSA. The entire data collection procedure is illustrated below (Fig. 1).

In the final phase, the cleansed CSV file was loaded in Orange version 3-3.38.0 for OMSA by selecting CSV file import under the data tab. The text mining option in the software was activated for sentiment analysis. Later, the corpus was activated for the Twitter data, and the corpus viewer was selected. The corpus viewer would list the details of the Tweets as documents from 1 to 357 along with the tweets. Later, the preprocessing was chosen and linked to the corpus. The preprocessing lets the users transform, tokenise, normalise, filter, etc., the dataset. Later, the sentiment analysis option was activated and linked to the preprocessed data. The Valence Aware Dictionary and sEntiment Reasoner (VADER) method was used for the present study. VADER is a rule-based sentiment analysis tool with a vocabulary that is especially useful for examining text sentiment on social media, such as online comments and tweets. It analyses a dictionary of words with positive or negative meanings and considers punctuation and capitalisation to determine a text's emotional subtlety[25]. Under the Transformation option, select columns were opened and checked for positive, negative, neutral, and compound sentiments. Later, the heat map was activated to show the feelings. The word cloud is also built by linking with the heat map. The result of the sentiment analysis was exported for the analysis. The procedure followed for executing the sentiment analysis is displayed in Fig. 2.

5. ANALYSIS AND INTERPRETATION

5.1 Webometric and Altmetric Features of the Sampled Articles

Table 1 shows the webometric and altmetric features of the sampled articles regarding Dimensions Citations (DC) and Altmetric Attention Score (AAS). The altmetric score is an aggregated score of mentions from different platforms. Only X mentions were assessed since the current study is related to Twitter and its activities. 1925 articles were indexed in the Altmetric Explorer

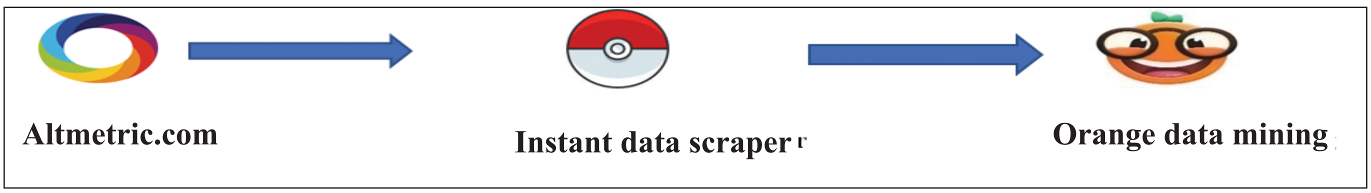

Figure 1. Data collection procedures with the tools used in each stage.

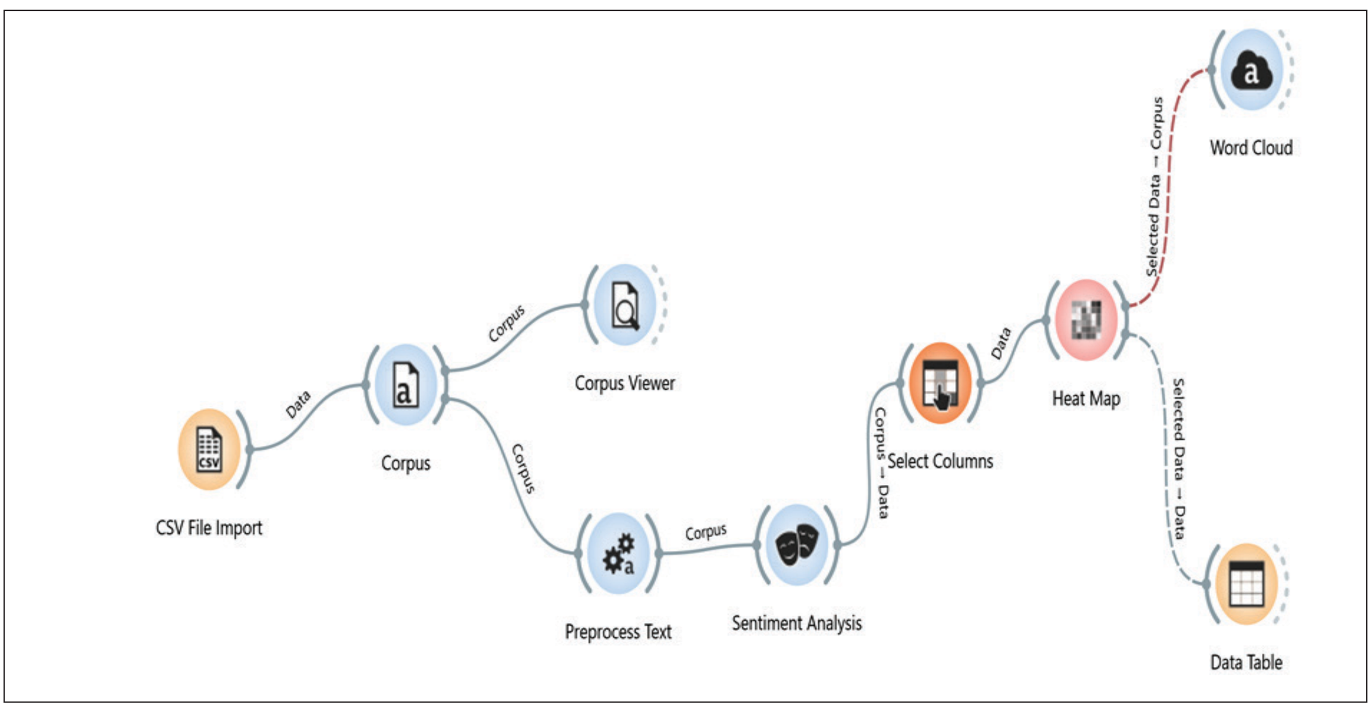

Figure 2. The overall approach of sentiment analysis.

with Twitter mentions, as discussed in the methodology section. It was understood that the number of articles with Twitter mentions increased as the years passed. From 1936 to 1998, 16 articles were found tweeted with 63 mentions. The articles got 515 DC while it garnered a 78 AAS. From 2000 to 2005, the number of articles with Twitter mentions was lower than in the previous period. For the 8 articles, DC accounted for 1915 while AAS accounted for 676. The highest number of DC, i.e., 177979 for the LIS article, was logged from 2016 to 2020, while for the AAS, it was from 2021 to 2024 with 108752. It is thus deduced that social media attention was more prevalent in recent articles.

5.2 Geographical Distribution of Tweets and Year-Wise Growth of X Mentions for LIS Research Outputs From India

The country-wise distribution of the X mentions in terms of tweets and retweets for all the LIS scholarly outputs (N=62995) is displayed in Fig. 3. A total of 237 countries across the globe mentioned LIS outputs through X platforms. The highest mentions were from the USA and UK, with 87969 and 44356 mentions from 78722 and 38434 Twitter handles. Canada and Spain stood in third and fourth place with mentions of 19046 and 18703, respectively. A good number of mentions, i.e., 14525, were clocked from India. Moreover, France, Australia, Germany, and Japan recorded 10,000+ Twitter activities. The least mentions were from 6 countries, including Mayotte, Christmas Island, Åland Islands, Tonga, Turks and Caicos Islands, and the Virgin Islands, with 1 mention recorded from a single account, respectively.

Figure 4 represents the growth of X mentions for India's LIS outputs (N=1925). Although Twitter mentions for the outputs have been traced from all over the globe since 1936, as shown in Table 1, India recorded the first mention in 2014 with 10 mentions, followed by 10 in 2015, 2 in 2016, and 6 in 2019. No Twitter mention was recorded in 2017 and 2018. The total number of mentions in 2020 was 20, while it was 32 in 2021. The highest mentions have been recorded recently, with 100 in 2023 and 160 in 2024.

5.3 Sentiment Analysis and a Word Cloud of Tweets

Figure 5 displays the heat map generated for the documents' sentiment analysis. The heat map has four columns representing the polarity as negative, positive, neutral, and a compound score, aggregating all three

Table 1. Webometric and altmetric features of the sampled articles

Year	N	DC	AAS	X mentions
1936-1998	16	515	78	63
2000-2005	8	1915	676	748
2006-2010	32	21372	4184	3408
2011-2015	346	29796	87807	95606
2016-2020	910	177979	39693	263054
2021-2024	613	9487	108752	172615
Total	**1925**	**241064**	**241190**	**535494**

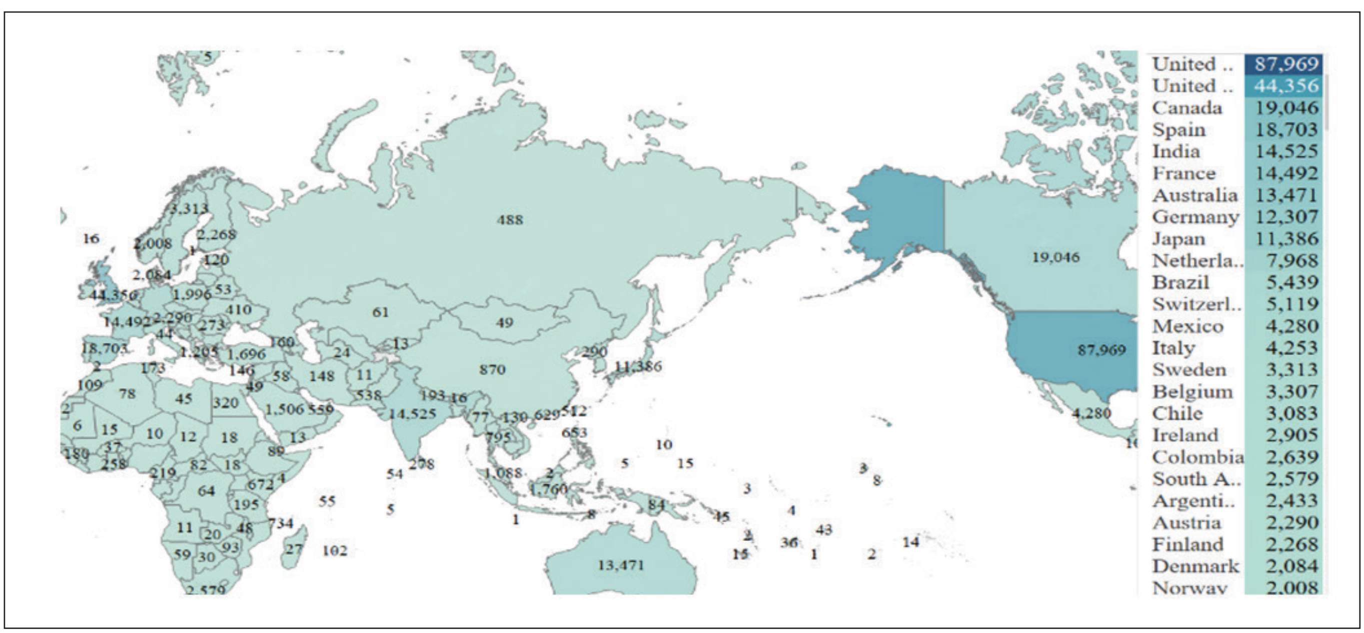

Figure 3. Geographical distribution of tweets for LIS research outputs.

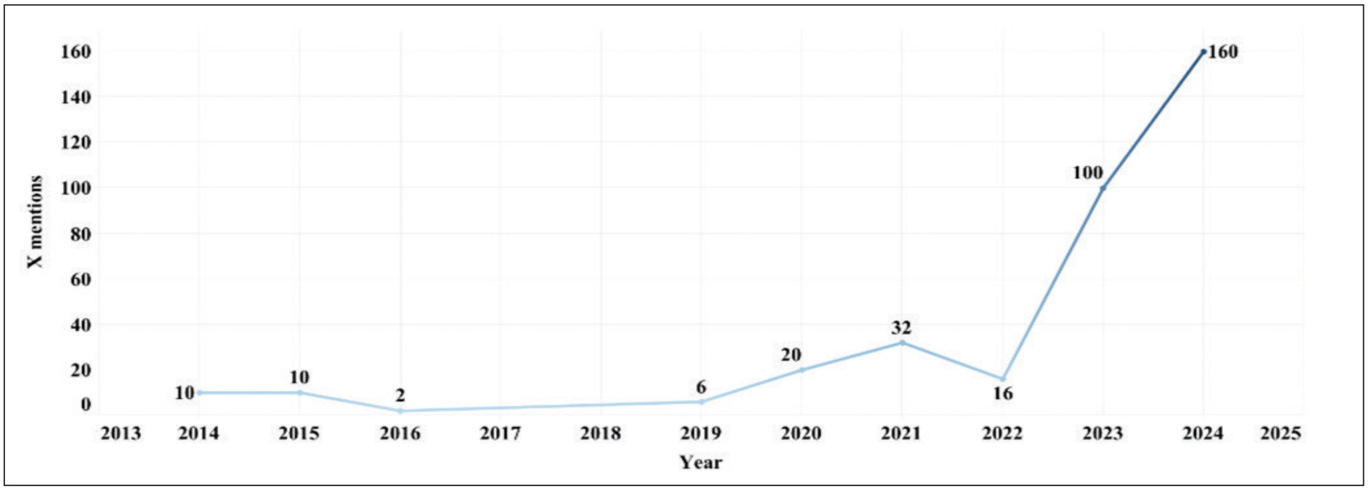

Figure 4. Year-wise distribution of twitter mentions from India.

sentiments. The yellow portion of the map represents the positive compound values of the positive documents, while the blue portion represents negative sentiments for the articles, as mentioned on Twitter. The sentiment analysis result has been presented as a table and uploaded to Figshare (https://figshare.com/articles/dataset/The_result_of_sentiment_analysis/28103390). As per the results from the heat map and Table, the average score of positive comments was 0.08, negative 0.06, and neutral 0.84, which indicated that most of the tweets were identified as neutral.

Figure 6 displays the most prominent words that have appeared while conversing about LIS research outputs on Twitter. The word cloud included words used to comment positively, negatively, and neutrally about the papers. As per the figure, the word research has been the dominant one with 100 weight, followed by paper with 50, science and India 48, publish 47, journal 45, read and one 38, review 36, access and article 28, peer and scientist 24, peer review 22, 18 Indian and impact, 15 open and government, 14 covid, 12 research journal and publish journal, 11 open access, etc.

5.4 Prediction of Citation Through Tweets

Twitter mentions comprise a significant share in deciding an article's total social media attention. Many studies have previously tried to assess whether early tweets can predict their upcoming citations in

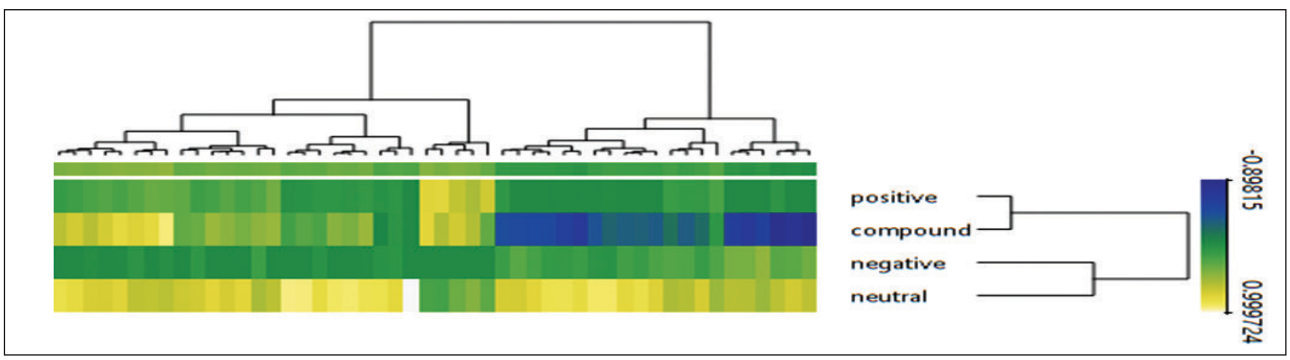

Figure 5. Heat map of sentiment analysis.

Figure 6. Wordcloud of dominant words used to converse about LIS papers.

Table 2. Prediction of citation through tweets

Predictor	Estimate	SE	t	p	r	r^2	f	p
Intercept	44.7599	9.7234	4.6	<.001	0.0599	0.00359	6.93	0.009
X mentions	0.031	0.0118	2.63	0.009				

different domains. To evaluate the same in library and information science, the data was subjected to linear regression by considering Tweets as an independent variable and citations as a dependent variable. The results, as per Table 2, discovered that early tweets could predict later citations for the LIS research since the p-value (.009) is less than the alpha value (.05). However, the r^2 value is .00359, which indicates 0.359 % of the variance, i.e., the model's independent variables are failing to account for the variation in the outcome variable adequately.

6. RESULTS AND DISCUSSION

Online access to scientific discussion lets people access scientific information produced across the globe. Twitter has been heralded for its capacity to boost public engagement with science. The present study has been conducted to assess the nature of Indians' scholarly communication on Twitter about LIS research. As far as the researcher knows, this is the first study to use Altmetric Explorer as a data source for the sentiment analysis of Twitter discussions on LIS research outputs.

The study reported interesting findings that were consistent with other previous studies. The study discovered that 102221 outputs were indexed in Explorer in the subject category of LIS, with 62995 (61.62 %) outputs having altmetrics. There was no significant difference regarding the citation and altmetric score for the LIS outputs. However, social media attention was higher for the outputs, with an excess of 126. Furthermore, it was observed that the latest articles got higher altmetrics than citations, supporting previous studies that found that citations take time to accrue[43&44].

Thus, altmetric score can be considered an indicator for swift evaluation of research[45-46]. Like citation and altmetric score, Twitter mentions were more prevalent for recent LIS articles. The possible reason for the fewer mentions of the older LIS articles could be the deletion of tweets or the closure of Twitter accounts, as reported by a previous study[47]. The country-wise analysis of the Twitter mentions deduced that most of the mentions were recorded from English-speaking countries since most of the investigated articles were published in the English language. In addition, the number of Twitter users is recorded as high in these countries[12,49]. Adding to this, 91 % of the scientific tweets globally are in English, as per the study findings of Yu[50], *et al*. Discussions from India regarding the LIS research on Twitter were fewer, which is consistent with the previous study findings of Patra[51].

The neutral sentiments of Twitter users about LIS research might be due to a lack of opinion or emotional expression while conversing about LIS research. Factual statements without expressing positive or negative feelings can also be a reason. If so, the VADER tool has a bias towards neutral sentiments.

The frequently appearing keywords while conversing about LIS research were analysed, and it was reported that the word "research" was the dominant one, followed by "paper." It indicated that the LIS scholarly community was tweeting more about their research and papers. Justifying this, previous studies have reported that Twitter has been a good channel for scholars to market their research[52-53].

Twitter can increase the impact of the research in terms of citations[54-55]. Finally, the study analysed whether metrics from Twitter could predict its upcoming citation since studies from other domains tried to prove the same[56-21,57].

The study results were consistent with the prior studies that showed that Twitter metrics could predict future citations for the LIS research outputs. Past studies have also reported that Twitter discussions could predict future retractions of articles. Thus, Twitter metrics can replace traditional metrics and be used wherever classic metrics are used for funding evaluation, faculty recruitment, promotion, etc.[59-60].

7. CONCLUSION

From the study's findings, scholarly communication of outputs on social media, especially Twitter, positively impacts the research. Channeling articles on Twitter helps to ameliorate the social impact of the study, thereby increasing its citations. The use of Twitter among the Indians, especially for scholarly communication, was found unsatisfactory. Thus, it is suggested that Indian authors can use Twitter to market their research outputs. The study's findings can be further reinforced by conducting extended studies exploring inner emotions like boredom, anger, excitement, disgust, etc., since the present study has delved only into three sentiments. Moreover, a similar study can be conducted on other social networking sites like Facebook, Google+, Reddit, YouTube, Wikipedia, Bluesky, etc. The Twitter discussion about LIS research from India did not occur often. Thus, considering other countries for the analysis would give a broader picture of the acceptability and popularity of the LIS research.

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CONTRIBUTOR

Dr. Vysakh. C is an Assistant Professor at the Department of Library and Information Science, Kannur University, Kerala. His areas of interest: Chiefly centred on Altmetrics, Meta-analysis, Sentiment analysis, Text mining, and Webometrics.