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Meta-Analysis of Associations Between Classic Metric and Altmetric Indicators of Selected LIS Articles

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ABSTRACT

Altmetrics or alternative metrics gauge the digital attention received by scientific outputs from the web, which is treated as a supplement to traditional citation metrics. In this study, we performed a meta-analysis of correlations between classic citation metrics and altmetrics indicators of library and information science (LIS) articles. We followed the systematic review method to select the articles and Erasmus Rotterdam Institute of Management Guidelines for reporting the meta-analysis results. To select the articles, keyword searches were conducted on Google Scholar, Scopus, and ResearchGate during the last week of November 2021. Eleven articles were assessed, and eight were subjected to meta-analysis following the inclusion and exclusion criteria. The findings reported negative and positive associations between citations and altmetric indicators among the selected articles, with varying correlation coefficient values from -.189 to 0.93. The result of the meta-analysis reported a pooled correlation coefficient of 0.47 (95% confidence interval, 0.339 to 0.586) for the articles. Sub-group analysis based on the citation source revealed that articles indexed on the Web of Science showed a higher pooled correlation coefficient (0.41) than articles indexed in Google Scholar (0.30). The study concluded that the pooled correlation between citation metrics with altmetric indicators was positive, ranging from low to moderate. The result of the study gives more insights to the scientometrics community to propose and use altmetric indicators as a proxy for traditional citation indicators for quick research impact evaluation of LIS articles.

Keywords: traditional metrics, citation metrics, altmetrics, citations, altmetric indicators, pooled correlation

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1. INTRODUCTION

Altmetrics or article-level metrics are alternative indicators that measure the social impact of scholarly outputs by gauging online discussion on research outputs from different platforms, chiefly social media, reference managers, news & policy documents, social bookmarking, and mainstream traditional media outlets (Ali, 2021; Daraio, 2021). Although altmetrics is a new concept, the investigation into altmetrics is escalating wildly compared to traditional citation metrics (Kwok, 2013). As a result, the debate on whether newly emerged social media metrics will replace traditional metrics for measuring impact is still going on. Many of the studies ratified that altmetrics can be used as a supplement for showing instantaneous societal impact along with scientific impact because of the positive association between these two metrics (Costas et al., 2015; Haustein et al., 2014b; Schlögl et al., 2014; Zhang et al., 2019; Zuccala et al., 2015). On the other hand, a handful of studies opposed this proposal, citing a negative and weak correlation (Chi et al., 2019; Gumpenberger et al., 2016; Haustein et al., 2014a; Thelwall et al., 2013). Since the magnitude of association between these metrics varies from weak to strong from domain to domain, it is unsure to conclude whether altmetrics can replace traditional metrics or can only be a complement due to positive correlation, or if it cannot replace or cannot complement due to negative correlation (Barnes, 2015; Thelwall, 2021). On account of all these issues, controversy still exists among the scientometric community across the globe and disciplines. The best solution is to pool the entirety of associations (both positive and negative) and vindicate the final pooled correlation coefficient (PCOR) by conducting a meta-analysis. Meta-analysis is usually employed to assess quantitative information from interconnected studies and generate results that encapsulate a whole body of research (Riley et al., 2011).

Studies assessing the pooled correlation between citation metrics and altmetrics have rarely been found in the scholarly world. Kolahi et al. (2021) reported a positive weak pooled correlation between citations and altmetric attention scores (AAS) (r=0.19; 95% confidence interval [CI], 0.12 to 0.25) when 27 health science-related studies were subjected to meta-analysis. In another comprehensive meta-synthesis, Bornmann (2015) reported the magnitude of the pooled correlation between citations and three social media indicators as negligible (microblogging, r=0.003), small (blog count, r=0.12), and medium to large (CiteULike, r=0.23 and Mendeley, r=0.51) after assessing a handful of studies that happened in prime disciplines. Other systematic reviews conducted by Patthi et al. (2017) and Araujo et al. (2021), by exploring outputs from various disciplines, primarily medical and health science, discovered a positive association between these two metrics.

As far as the library and information science (LIS) domain is concerned, a few studies were found narrating the association between traditional metrics and social media metrics under the article category of 'review / systematic reviews' (Borah & Madhusudhan, 2022; Sugimoto et al., 2017; Tahamtan & Bornmann, 2020). However, the longstanding debate of whether the new generation metrics replace or complement the old citation metrics has been extended to the LIS domain too, and no attempt with a meta-analysis approach has been undertaken hitherto to contribute to this debate. Thus, the present study bridges this gap by pooling the correlation reported in LIS outputs between citation metrics and social media indicators. The value of the pooled correlation decides whether they are positively or negatively correlated, and also at what magnitude for the outputs would contribute to the current dispute in general and LIS discipline in specific.

1.1. Objectives of the Study

The primary objective of this study is:

- To conduct a meta-analysis of the association between citations and altmetric indicators of the selected LIS research articles

The study has a secondary objective as follows:

- To conduct a meta-analysis of the association between citations and altmetric indicators of the selected LIS articles based on the source of citations

2. METHODS

2.1. Formatting the Review Question and Outcome

The review question is framed to determine the PCOR between classic metric and altmetric indicators of the LIS articles that satisfies the eligibility criteria.

2.2. Search Strategy

Mainly Google Scholar, Scopus, and ResearchGate databases were searched for articles collected during the last week of November 2021. The keywords included 'Altmetrics of LIS articles,' 'Altmetrics of library and information science articles,' and 'Correlation between citations and altmetric indicators of LIS articles,' which were carried out as free searches in Google Scholar and ResearchGate, and in 'Search within' fields as 'article title, abstracts, keywords'

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in the Scopus database.

2.3. Eligibility, Inclusion, and Exclusion Criteria

The LIS articles were selected following the systematic review guidelines (Sensuse et al., 2021). Later, documents were identified and screened through Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines (Fig. 1). Only peer-reviewed articles published in the English language were considered. Other research outputs like review articles, letters, and articles in press and conference papers were excluded since these research outputs did not have enough altmetrics for the analysis. Also, studies did not take place at large in the LIS domain. Furthermore, those articles which inquire about the association between classic metric indicators and social media metric indicators were considered. For conducting the meta-analysis, articles that attempted to correlate traditional citation indicators, majorly 'citations' (journal impact factor [Art. no. 4] and impact points [Art. no. 3] in the absence of citations) with social media indicators, primarily 'altmetric attention scores (AAS)' (Mendeley metrics [Art. no. 1], Twitter mentions [Art. no. 2], ResearchGate score (RG score) [Art. no. 3], and social media indicators [Art. no. 5] in the absence of AAS) were considered. RG score has been treated as a significant source of altmetrics in this study after referring to previously published articles (Ahmad, 2019; Shrivastava & Mahajan, 2015). Studies with sub-studies (Art. nos. 7 & 8) and those not having identical/standalone traditional or social media indicators like 'citations' or 'altmetric attention score' (Art. no. 11) were excluded from the meta-analysis. Contrary to Article 11 (Art. no. 11), the first and second article (Art. nos. 1 & 2) have been taken for the meta-analysis after considering that the study tried to correlate Mendeley and Twitter metrics chiefly against classic indicators (See Table 1 for details). Articles having no keywords such as 'Altmetrics of LIS' or 'Correlation between citations and altmetric indicators of LIS' in the title were also included (Art. nos. 1, 2 & 4) after acknowledging that the article tried to correlate citation indicators with altmetric indicators (Mendeley or Twitter) predominantly.

2.4. Meta-Analysis

The meta-analysis was carried out by using two major

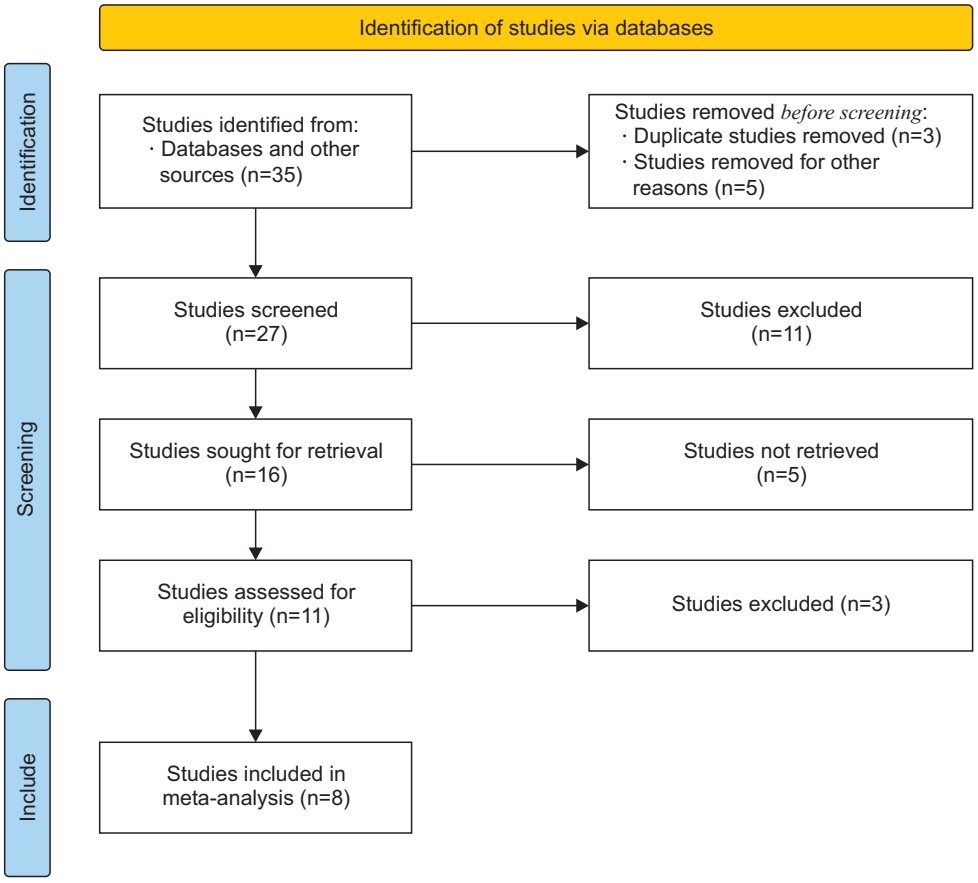

Fig. 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) flow diagram.

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Table 1. Characteristics/details of the articles selected for the study (including excluded studies)

Article/ studies no.	Authors and year of publication	Title	Journal	Source of citations	Methods followed	Correlation conducted between	Correlation value	Findings	Meta-analysis conducted between
1	Mohammadi and Thelwall (2014)	Mendeley readership altmetrics for the social sciences and humanities: Research evaluation and knowledge flows	Journal of the Association for Information Science and Technology	WoS	Samples- 2,552 LIS articles indexed in 2008. Correlation- Spearman	Citations with Mendeley metrics	rho=.369	Positive correlation	Citations with Mendeley metrics
2	Zhao and Wolfram (2015)	Assessing the popularity of the top-tier journals in the LIS field on Twitter	Proceedings of the Association for Information Science and Technology	WoS	Samples- 30 Top tier LIS journals as per JCR ranks published in 2013. Correlation- Spearman	Twitter mentions with i. Total cites ii. Impact factor iii. 5-year impact factor iv. Immediacy index v. Articles vi. Cited half-life vii. Eigen factor score viii. Article influence score	i. rho=.169 ii. rho=.074 iii. rho=-.010 iv. rho=.202 v. rho=.178 vi. rho=-.189 vii. rho=.364 viii. rho=.043	Positive and negative correlations	Total cites with Twitter mentions
3	Ali and Richardson (2017)	Pakistani LIS scholars' altmetrics in ResearchGate	Program: Electronic Library and Information Systems	RG	Samples- 78 RG profiles through purposive sampling. Correlation- Spearman	Impact points with RG score	rho=.903	Positive correlation	Impact points with RG score
4	Htoo and Na (2017)	Disciplinary differences in altmetric for social sciences	Online Information Review	WoS	Samples-19,580 articles published from 2008 to 2013. Correlation- Pearson	Journal impact factor with i. AAS i. Mendeley ii. Twitter iii. CiteULike iv. Facebook v. Blogs vi. News vii. Google+ viii. Reddit ix. F1000 x. Pinners	i. r=0.49 ii. r=0.58 iii. r=0.08 iv. r=0.37 v. r=0.09 vi. r=0.20 vii. r=0.09 viii. r=0.20 ix. r=0.25 x. -	Positive correlation	Journal impact factor with AAS

Table 1. Continued

Article/ studies no.	Authors and year of publication	Title	Journal	Source of citations	Methods followed	Correlation conducted between	Correlation value	Findings	Meta-analysis conducted between
5	Saberi and Ekhtiyari (2019)	Usage, captures, mentions, social media and citations of LIS highly cited papers: an altmetrics study	Performance Measurement and Metrics	GS	Samples- 10 LIS classic papers in 2006. Correlation- Spearman	Citations with i. Usage metrics ii. Capture metrics iii. Mentions metrics iv. Social media metrics v. Citations metrics	i. rho=.450 ii. rho=.683 iii. rho=.366 iv. rho=.162 v. rho=.950	Positive correlation	Citations with social media metrics
6	Ezema and Ugwu (2019)	Correlating research impact of library and information science journals using citation counts and altmetrics attention	Information Discovery and Delivery	WoS GS Scopus	Samples- 18 LIS journals with high altmetric attention. Correlation- Pearson	Citations from WoS, GS and Scopus with AAS	r=.444 r=.531 r=.733	Positive correlation	Citations with AAS
7	Verma and Madhusudhan (2019a)	Altmetric analysis of highly cited publications on digital library in Brazil and India: a comparative study	Library Philosophy and Practice	WoS	Samples- 10 articles on Digital Library Published from India and Brazil. Correlation- Spearman	Citations with AAS i. Brazil ii. India	i. rho=-0.2 ii. rho=-0.11	Negative correlation	Excluded
8	Verma and Madhusudhan (2019b)	An altmetric comparison of highly cited digital library publications of India and China	Annals of Library and Information Studies	WoS	Samples- Top 10 highly cited articles on 'digital library' from India and China. Correlation- Spearman	Citations with AAS i. India ii. China	i. rho=-0.11 ii. rho=0	Negative correlation and no correlation	Excluded

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Table 1. Continued

Article/ studies no.	Authors and year of publication	Title	Journal	Source of citations	Methods followed	Correlation conducted between	Correlation value	Findings	Meta-analysis conducted between
9	Vysakh and Rajendra Babu (2021)	Altmetrics linked scholarly information from Dimensions.ai datasets for the top 100 LIS articles	SRELS Journal of Information Management	Dimensions	Samples- 100 highly cited LIS articles. Correlation- Spearman	Citations with AAS	rho=0.19	Positive correlation	Citations with AAS
10	Rangaswamy and Rajendra Babu (2021)	A correlation comparative analysis of top articles in library and information science using citation and altmetric attention scores	SRELS Journal of Information Management	GS	Samples- 100 top cited articles from top 10 LIS journals. Correlation- Spearman	Citation with AAS	rho=-.106	Negative correlation	Citation with AAS
11	Cho (2021)	Altmetrics analysis of highly cited academic papers in the field of Library and information science	Scientometrics	WoS	Samples-Highly cited 1,000 articles in the LIS sub-domain. Correlation- Pearson	Citations with i. Usage view ii. Capture readers iii. Blog mention iv. Reference mention v. Social media tweet	i. r=.03 ii. r=.29 iii. r=-.00 iv. r=.01 v. r=-.04	Positive and negative correlations	Excluded

LIS, library and information science; WoS, Web of Science; RG, ResearchGate; GS, Google Scholar; JCR, Journal Citation Reports; AAS, altmetric attention score.

software packages, viz. MedCalc 20.015 (trial version) and Meta-Mar, a free online meta-analysis service accessible at https://www.meta-mar.com. The minimum number of samples for carrying out a meta-analysis is two (Israel & Richter, 2011; Ryan, 2016), and in Meta-Mar it was four, and the correlation coefficient ranged from zero to one (Meta-Mar, 2021). The effect sizes were computed by using Fisher's transformation of correlations. The formula to transform r to a z-score is z'=.5[ln(1+r)–ln(1-r)] (Statistics How To, 2022). Data were analyzed using the random effects model (REM) since the study involved considerable heterogeneity (I^2>75%, p<0.05). The value of heterogeneity varies from 0 to 100% and can be treated as 25% low heterogeneity, 50% medium heterogeneity, and 75% high/considerable heterogeneity (Higgins et al., 2003).

2.5. Characteristics of the Included Studies

The result according to Table 1 shows that out of eleven studies, five studies (Cho, 2021; Ezema & Ugwu, 2019; Htoo & Na, 2017; Saberi & Ekhtiyari, 2019; Zhao & Wolfram, 2015) had sub-studies by correlating citations with other altmetric indicators. As opposed to these studies, Mohammadi and Thelwall (2014), Ali and Richardson (2017), Vysakh and Rajendra Babu (2021), and Rangaswamy and Rajendra Babu (2021) examined the correlation between two prime indicators, i.e., citations and AASs. Furthermore, the studies were based on citations from different databases, majorly Web of Science and Google Scholar, and the total sample size accounted for 22,468. The studies reported negative and positive associations once citation indicators correlated against different altmetric indicators. Two correlation methods, i.e., Spearman and Pearson, were recognized and the correlation value ranged from -.189 to 0.93.

3. RESULTS

Following the guidelines given by Erasmus Rotterdam Institute of Management for interpreting meta-analysis results (Hak et al., 2022), firstly we present a forest plot for all the articles with pooled correlation and heterogeneity; secondly, forest plots for subgroup analysis based on the source of citations, and finally, a funnel plot for exhibiting the publication bias among the articles selected for the analysis.

3.1. Meta-Analysis for All the Included Articles

Meta-analysis was carried out between the classic metric indicators and social media metric indicators of the eight eligible LIS articles. Fig. 2 shows the forest plot for the meta-analysis. The X-axis shows the correlation coefficient values of each study. The Y-axis shows the corresponding study's lead author and year of publication. The size of the boxes in blue colour shows the number of samples, and a larger size represents a higher sample size. The blue diamonds represent the investigated articles' total fixed and random effects. In the meta-analysis, the fixed-effect model assumes the underlying effect is the same across all studies, and the REM assumes heterogeneous effects across studies (Mantel & Haenszel, 1959; DerSimonian & Laird, 1986). The aggregate samples from all eight studies were 22,468. Except for one article, i.e., Rangaswamy and Rajendra Babu (2021), all other remaining studies reported a positive correlation. The highest positive correlation was observed for the fifth and third studies, i.e., Saberi and Ekhtiyari (2019) (rho=0.95) and Ali and Richardson (2017) (rho=0.90) (Appendix 1).

3.2. Pooled Correlation and Heterogeneity

As per Table 2, the PCOR was 0.47 (95% CI, 0.339 to

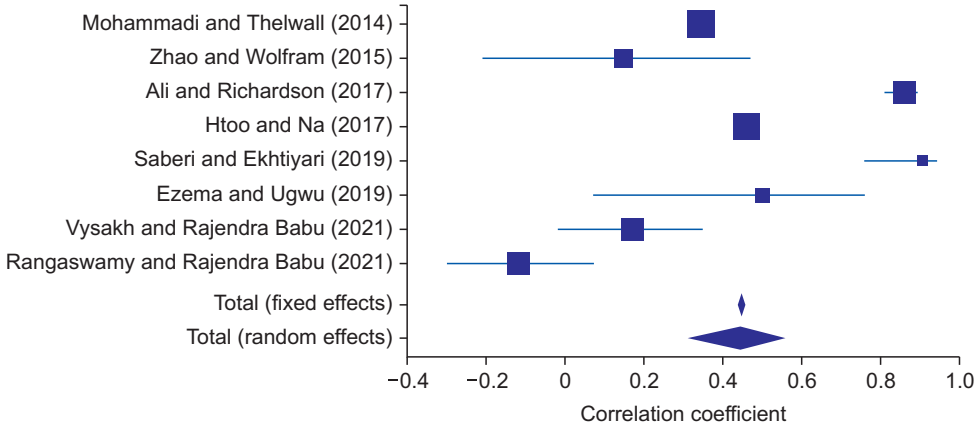

Fig. 2. Forest plot for the meta-analysis.

Table 2. Pooled correlation and heterogeneity

	n	Fisher Z	r	SE	95% CI	z sore	*p*-value	Heterogeneity
Random effect model	22,468	0.51	0.47	0.081	0.339, 0.586	6.308	0	I^2=96.2%, Tau^2=0.035

SE, standard error; CI, confidence interval.

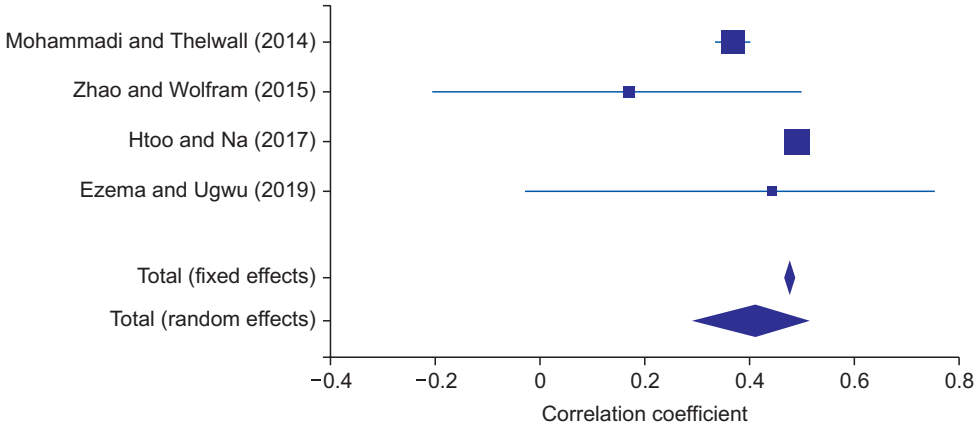

Fig. 3. Meta-analysis of articles from Web of Science.

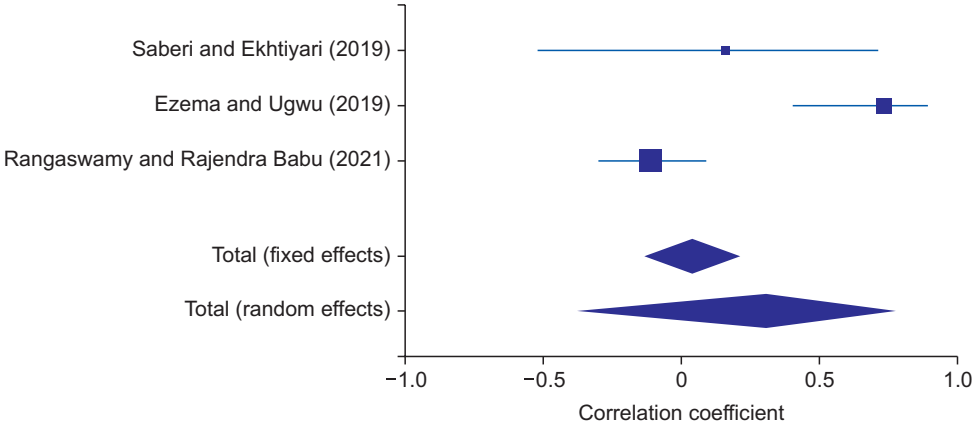

Fig. 4. Meta-analysis of articles from Google Scholar.

0.586) for the REM. The general heterogeneity was high for the articles (I^2=96.2%), representing the variability in the selected studies. If the heterogeneity is very high, the REM is nearly equal regardless of the number of samples reporting a meta-analytic summary close to the more easily calculated arithmetic mean of each study's results.

3.3. Sub-Group Analysis Based on the Source of Citations

Since the overall meta-analysis result showed considerable heterogeneity, sub-group analysis was carried out to know the correlation variation based on the source of citations. For this purpose, four articles whose source of citations is from Web of Science (Fig. 3) and three articles whose source of citations is from Google Scholar (Fig. 4) were subjected to the analysis, including articles having sub-studies (Ezema & Ugwu, 2019). The remaining two studies, i.e., Ali and Richardson (2017) and Vysakh and Rajendra Babu (2021) were not considered owing to the lack of number of studies to carry out meta-analysis based on the source of citations. The result showed that the PCOR for Web of Science articles was 0.41 (95% CI, 0.292 to 0.515), and for Google Scholar, it was 0.30 (95% CI, -0.373 to 0.771).

3.4. Publication Bias

Fig. 5 and Appendix 2 demonstrate the funnel plot and the result of Egger's test and Begg's test applied to deter-

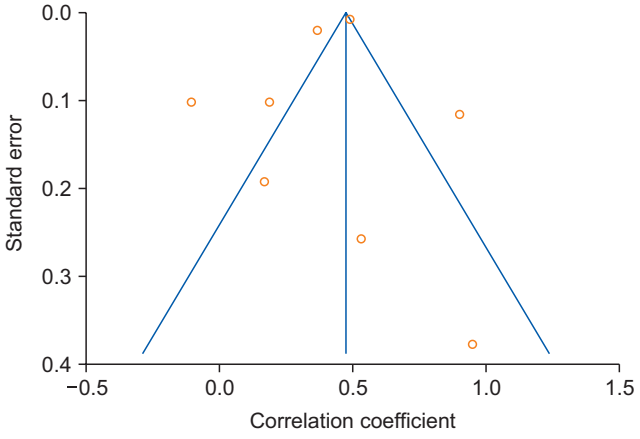

Fig. 5. Funnel plot for publication bias.

mine the publication bias in the articles selected for the study. The symmetry of the diagram shows that no publication bias existed, and Egger's (p-value=0.82) and Begg's test (p-value=0.25) confirmed the same since the p-value stood higher than 0.05 (p>0.05).

4. FINDINGS AND DISCUSSION

To our best knowledge, this is the first meta-analysis to quantify the pooled correlation between classic metric indicators and altmetric indicators of LIS research articles. We estimated the pooled correlation between citation metric indicators from five prime databases: Web of Science, Google Scholar, Scopus, Dimensions, and ResearchGate (as a source of altmetrics also), with the altmetric indicators of selected eight articles published between 2014 and 2021. The articles qualified for meta-analysis exhibited positive and negative correlations between citation indicators with various altmetric indicators and had considerable heterogeneity (I^2=96.2%). As a result, we followed the REM for the analysis. Israel and Richter (2011) opined that "there are no accepted guidelines for when a meta-analysis should not be completed due to statistical heterogeneity, and it is left to the author's discretion to determine if a meta-analysis is appropriate." The result of the REM exhibited a PCOR of 0.47 (95% CI, 0.339 to 0.586) between citation indicators with altmetric indicators, which are treated as a medium correlation (Cohen, 1988).

When we carried out the sub-group analysis based on the source of citations, we discovered that articles indexed on the Web of Science showed a higher PCOR (0.41) than articles indexed in Google Scholar (0.30). The possible reason for this could be that the articles indexed in the Web of Science subjected to analysis include higher samples than those indexed in Google Scholar. In addition, the negative correlation of one article (Art. no. 10) estimated at -.106 as per the Spearman correlation indexed on Google Scholar could also be a possible reason.

We also inspected the publication bias among the articles through funnel plot and Eggers and Begg's test. The reason for conducting the Eggers test was that if the study involved considerable heterogeneity and the number of articles was less than ten, the visual inspection of the funnel plot would not be enough to interpret the publication bias. Therefore, the Eggers test will be preferred (Simmonds, 2015). The result of the tests discovered zero publication bias since Egger's test for a regression intercept reported a p-value of 0.82, and Begg's test for rank correlation demonstrated a p-value of 0.25.

5. CONCLUSION

Studies galore have investigated the association between traditional metrics and altmetrics to decide the novelty of the newly emerged social media metrics to use as a replacement or supplement to measure the immediate and broad impact of research. The association between these metrics varied from positive to negative (weak to strong) from domain to domain. As per our study findings, the PCOR shows a low (sub-group analysis) to a medium association (for all the articles, Fig. 2) for LIS articles. Thus it can be concluded that for LIS articles, the AAS and other significant indicators, i.e., Mendeley and Twitter, show similar characteristics to traditional citation metric indicators. Thus it can be used as a proxy for measuring the immediate invisible impact of LIS research articles.

The present study has some limitations. First, the study is limited to conducting meta-analysis between citation indicators with a few altmetric indicators, as explained in the 'eligibility, inclusion and exclusion criteria' section. Out of the eleven studies, three were omitted from subjecting to overall meta-analysis even though two studies tried to correlate citation with altmetric score but have had sub-studies (Verma & Madhusudhan, 2019a, 2019b). Contrary to this, studies having sub-studies were also considered for sub-group analysis based on the source of citations. Another possibility for sub-group analysis by considering sampling methods has not been explored. Future studies can observe how the correlation between citation and altmetric indicators varies over time.

Furthermore, a comprehensive meta-synthesis should be conducted between classic and social metric indicators

to understand the existing friction better. Similar meta-analyses or syntheses can be conducted in other domains to understand whether altmetrics exhibits the same feature as classic metrics. If so, the potential of the newly emerged social media metrics in the quick social impact evaluation of research in that particular domain can be substantiated.

CONFLICTS OF INTEREST

No potential conflict of interest relevant to this article was reported.

REFERENCES

Ahmad, Z. (2019). Profiles of AMU and JNU researchers on Researchgate: An altmetric analysis. *Kelpro Bulletin,* 23(1), 101-112. https://www.academia.edu/42459122/Profiles_of_AMU_and_JNU_Researchers_on_Researchgate_An_Altmetric_Analysis.

Ali, M. J. (2021). Understanding the altmetrics. *Seminars in Ophthalmology,* 36(5-6), 351-353. https://doi.org/10.1080/08820538.2021.1930806.

Ali, M. Y., & Richardson, J. (2017). Pakistani LIS scholars' altmetrics in ResearchGate. *Program,* 51(2), 152-169. https://doi.org/10.1108/PROG-07-2016-0052.

Araujo, A. C., Vanin, A. A., Nascimento, D. P., Gonzalez, G. Z., & Costa, L. O. P. (2021). What are the variables associated with Altmetric scores? *Systematic reviews,* 10(1), 193. https://doi.org/10.1186/s13643-021-01735-0.

Barnes, C. (2015). The use of altmetrics as a tool for measuring research impact. *Australian Academic & Research Libraries,* 46(2), 121-134. https://doi.org/10.1080/00048623.2014.1003174.

Borah, R., & Madhusudhan, M. (2022). A literature review of research articles on altmetrics. In K. S. Shivraj, A. A. Suleiman, & P. Gupta (Eds.), *Knowledge management in higher education institutions* (pp. 174-181). Manipal University Jaipur.

Bornmann, L. (2015). Alternative metrics in scientometrics: A meta-analysis of research into three altmetrics. *Scientometrics,* 103(3), 1123-1144. https://doi.org/10.1007/s11192-015-1565-y.

Chi, P. S., Gorraiz, J., & Glänzel, W. (2019). Comparing capture, usage and citation indicators: an altmetric analysis of journal papers in chemistry disciplines. *Scientometrics,* 120(3), 1461-1473. https://doi.org/10.1007/s11192-019-03168-y.

Cho, J. (2021). Altmetrics analysis of highly cited academic papers in the field of library and information science. *Scientometrics,* 126(9), 7623-7635. https://doi.org/10.1007/s11192-021-04084-w.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. 2nd ed. Routledge.

Costas, R., Zahedi, Z., & Wouters, P. (2015). Do "altmetrics" correlate with citations? Extensive comparison of altmetric indicators with citations from a multidisciplinary perspective. *Journal of the Association for Information Science and Technology,* 66(10), 2003-2019. https://doi.org/10.1002/asi.23309.

Daraio, C. (2021). Altmetrics as an answer to the need for democratization of research and its evaluation. *Journal of Altmetrics,* 4(1), 5. https://doi.org/10.29024/joa.43.

DerSimonian, R., & Laird, N. (1986). Meta-analysis in clinical trials. *Controlled Clinical Trials,* 7(3), 177-188. https://doi.org/10.1016/0197-2456(86)90046-2.

Ezema, I. J., & Ugwu, C. I. (2019). Correlating research impact of library and information science journals using citation counts and altmetrics attention. *Information Discovery and Delivery,* 47(3), 143-153. https://doi.org/10.1108/IDD-08-2018-0029.

Gumpenberger, C., Glänzel, W., & Gorraiz, J. (2016). The ecstasy and the agony of the altmetric score. *Scientometrics,* 108(2), 977-982. https://doi.org/10.1007/s11192-016-1991-5.

Hak, T., Van Rhee, H. J., & Suurmond, R. (2022). *How to interpret results of meta-analysis. (Version 1.0).* https://www.erim.eur.nl/research-support/meta-essentials/interpret-results.

Haustein, S., Bowman, T. D., Holmberg, K., Peters, I., & Larivière, V. (2014a). Astrophysicists on Twitter: An in-depth analysis of tweeting and scientific publication behavior. *Aslib Journal of Information Management,* 66(3), 279-296. https://doi.org/10.1108/AJIM-09-2013-0081.

Haustein, S., Peters, I., Bar-Ilan, J., Priem, J., Shema, H., & Terliesner, J. (2014b). Coverage and adoption of altmetrics sources in the bibliometric community. *Scientometrics,* 101(2), 1145-1163. https://doi.org/10.1007/s11192-013-1221-3.

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ,* 327(7414), 557-560. https://doi.org/10.1136/bmj.327.7414.557.

Htoo, T. H. H., & Na, J. C. (2017). Disciplinary differences in altmetrics for social sciences. *Online Information Review,* 41(2), 235-251. https://doi.org/10.1108/OIR-12-2015-0386.

Israel, H., & Richter, R. R. (2011). A guide to understanding meta-analysis. *The Journal of orthopaedic and sports physical therapy,* 41(7), 496-504. https://doi.org/10.2519/

jospt.2011.3333.

Kolahi, J., Khazaei, S., Iranmanesh, P., Kim, J., Bang, H., & Khademi, A. (2021). Meta-analysis of correlations between altmetric attention score and citations in health sciences. *BioMed Research International,* 2021, 6680764. https://doi.org/10.1155/2021/6680764.

Kwok, R. (2013). Research impact: Altmetrics make their mark. *Nature,* 500(7463), 491-493. https://doi.org/10.1038/nj7463-491a.

Mantel, N., & Haenszel, W. (1959). Statistical aspects of the analysis of data from retrospective studies of disease. *Journal of the National Cancer Institute,* 22(4), 719-748. https://doi.org/10.1093/jnci/22.4.719.

Meta-Mar. (2021). *Meta-analysis: Correlation model.* https://meta-mar.shinyapps.io/meta-analysis-calculator/.

Mohammadi, E., & Thelwall, M. (2014). Mendeley readership altmetrics for the social sciences and humanities: Research evaluation and knowledge flows. *Journal of the Association for Information Science and Technology,* 65(8), 1627-1638. https://doi.org/10.1002/asi.23071.

Patthi, B., Prasad, M., Gupta, R., Singla, A., Kumar, J. K., Dhama, K., Ali, I., & Niraj, L. K. (2017). Altmetrics - A collated adjunct beyond citations for scholarly impact: A systematic review. *Journal of Clinical and Diagnostic Research,* 11(6), ZE16-ZE20. https://doi.org/10.7860/JCDR/2017/26153.10078.

Rangaswamy, B., & Rajendra Babu, H. (2021). A correlation comparative analysis of top articles in library and information science using citation and altmetric attention scores. *SRELS Journal of Information Management,* 58(3), 157-164. https://doi.org/10.17821/srels/2021/v58i3/158132.

Riley, R. D., Higgins, J. P., & Deeks, J. J. (2011). Interpretation of random effects meta-analyses. *BMJ,* 342, d549. https://doi.org/10.1136/bmj.d549.

Ryan, R. (2016). *Cochrane consumers and communication group reviews: Meta-analysis.* http://cccrg.cochrane.org/sites/cccrg.cochrane.org/files/public/uploads/meta-analysis_revised_december_1st_1_2016.pdf.

Saberi, M. K., & Ekhtiyari, F. (2019). Usage, captures, mentions, social media and citations of LIS highly cited papers: An altmetrics study. *Performance Measurement and Metrics,* 20(1), 37-47. https://doi.org/10.1108/PMM-10-2018-0025.

Schlögl, C., Gorraiz, J., Gumpenberger, C., Jack, K., & Kraker, P. (2014). Comparison of downloads, citations and readership data for two information systems journals. *Scientometrics,* 101(2), 1113-1128. https://doi.org/10.1007/s11192-014-1365-9.

Sensuse, D. I., Lestari, P. I., & Hakim, S. A. (2021). Exploring factors influencing knowledge sharing mechanisms and technology to support the collaboration ecosystem: A review. *DESIDOC Journal of Library & Information Technology,* 41(3), 226-234. https://doi.org/10.14429/djlit.41.03.16609.

Shrivastava, R., & Mahajan, P. (2015). Relationship amongst ResearchGate altmetric indicators and Scopus bibliometric indicators: The case of Panjab University Chandigarh (India). *New Library World,* 116(9/10), 564-577. https://doi.org/10.1108/NLW-03-2015-0017.

Simmonds, M. (2015). Quantifying the risk of error when interpreting funnel plots. *Systematic Reviews,* 4, 24. https://doi.org/10.1186/s13643-015-0004-8.

Statistics How To. (2022). *What is Fisher Z-Transformation?* https://www.statisticshowto.com/fisher-z.

Sugimoto, C. R., Work, S., Larivière, V., & Haustein, S. (2017). Scholarly use of social media and altmetrics: A review of the literature. *Journal of the Association for Information Science and Technology,* 68(9), 2037-2062. https://doi.org/10.1002/asi.23833.

Tahamtan, I., & Bornmann, L. (2020). Altmetrics and societal impact measurements: Match or mismatch? A literature review. *Profesional De La información,* 29(1). https://doi.org/10.3145/epi.2020.ene.02.

Thelwall, M. (2021). Measuring societal impacts of research with altmetrics? Common problems and mistakes. *Journal of Economic Surveys,* 35(5), 1302-1314. https://doi.org/10.1111/joes.12381.

Thelwall, M., Haustein, S., Larivière, V., & Sugimoto, C. R. (2013). Do altmetrics work? Twitter and ten other social web services. *PLoS One,* 8(5), e64841. https://doi.org/10.1371/journal.pone.0064841.

Verma, S., & Madhusudhan, M. (2019a). Altmetric analysis of highly cited publications on digital library in Brazil and India: A comparative study. *Library Philosophy and Practice,* 2273. https://digitalcommons.unl.edu/libphilprac/2273.

Verma, S., & Madhusudhan, M. (2019b). An altmetric comparison of highly cited digital library publications of India and China. *Annals of Library and Information Studies,* 66(2), 71-75. https://core.ac.uk/download/pdf/229208328.pdf.

Vysakh, C., & Rajendra Babu, H. (2021). Altmetrics linked scholarly information from Dimensions.ai datasets for the top 100 LIS articles. *SRELS Journal of Information Management,* 58(3), 197-208. https://doi.org/10.17821/srels/2021/v58i3/158563.

Zhang, X., Wang, X., Zhao, H., de Pablos, P. O., Sun, Y., & Xiong, H. (2019). An effectiveness analysis of altmetrics indices for different levels of artificial intelligence publications. *Scientometrics,* 119(3), 1311-1344. https://doi.org/10.1007/s11192-019-03088-x.

Zhao, Y., & Wolfram, D. (2015). Assessing the popularity of the top-tier journals in the LIS field on Twitter. *Proceedings of the Association for Information Science and Technology,* 52(1), 1-4. https://doi.org/10.1002/pra2.2015.145052010092.

Zuccala, A. A., Verleysen, F. T., Cornacchia, R., & Engels, T. C. E. (2015). Altmetrics for the humanities: Comparing Goodreads reader ratings with citations to history books. *Aslib Journal of Information Management,* 67(3), 320-336. https://doi.org/10.1108/AJIM-11-2014-0152.

APPENDICES

Appendix 1. Result of meta-analysis

Article no.	Correlation (r)	Samples (n)	Standard error	r_lower	r_upper	Fisher z	Weight(%) _fixed	Weight(%) _random
1	0.36	2,552	0.019	0.330	0.407	0.387	11.357	18.731
2	0.16	30	0.192	-0.208	0.546	0.170	0.120	9.186
3	0.90	78	0.115	0.676	1.129	1.488	0.334	13.703
4	0.49	19,580	0.007	0.475	0.504	0.536	87.225	18.914
5	0.95	10	0.377	0.209	1.690	1.831	0.031	3.717
6	0.53	18	0.258	0.024	1.037	0.591	0.066	6.506
9	0.19	100	0.101	-0.009	0.389	0.192	0.432	14.620
10	-0.10	100	0.101	-0.305	0.093	-0.106	0.432	14.620

Appendix 2. Egger's and Begg's test for publication bias

Egger's test	
Intercept	-0.54
95% CI	-6.2328 to 5.1353
Significance level	p=0.82
Begg's test	
Kendall's Tau	0.32
Significance level	p=0.25

CI, confidence interval.