Altmetrics indicators for institutional performance assessment: Does a relationship with traditional indicators exist?

Solanki Gupta[1, 2], Abhirup Nandy[1], Hiran H. Lathabai[3], Nilabhra Rohan Das[4], Vivek Kumar Singh[1, 5,6]

[1]Department of Computer Science, Banaras Hindu University, Varanasi, India

[2]School of Engineering and Technology, KR Mangalam University, Gurugram-122103, India

[3] Amrita CREATE, Amrita Vishwa Vidyapeetham, Amritapuri-690525, Kerala, India

[4]Bristol Medical School, University of Bristol, Bristol, UK.

[5]Department of Computer Science, University of Delhi, Delhi-110007, India

[6]Delhi School of Analytics, University of Delhi, Delhi-110007, India.

ABSTRACT: *Scientometricians are exploring altmetrics in different contexts. Its potential as an early impact assessment tool and possible predictor of future impact is one of the most widely explored themes in altmetric research. Many studies explored the relationship between altmetrics and traditional indicators. But relationships at the level of actors of science and technology, like individual scholars, institutions, etc., remain underexplored. In this work, we attempt to study the relationship at the institutional level using the top 135 productive Indian institutions. Explorations carried out include both raw as well as derived indicators. Mendeley reads is found to be the most promising raw altmetric indicator. It is also determined as the suitable source to derive many derived indicators. The potential of recently introduced indicators like* ψ, x *and* x_d *to be used for creating derived altmetric indicators is also revealed. Avenues for further research that may strengthen the usefulness of altmetrics are also discussed.*

Keywords: Performance Assessment, Bibliometric Indicators, Altmetric Indicators

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1. Introduction

Altmetrics, or alternative metrics, is revolutionising scholarly impact assessment beyond traditional citations, encompassing public engagement indicators like social media mentions, downloads, views, and discussions (Fenner, 2013; Piwowar & Priem, 2013; Shema et al., 2014). This paradigm shift, termed Scientometric 2.0 (Priem & Hemminger, 2010), acknowledges the evolving digital landscape, emphasizing broader impact assessment in addition to traditional citation-based metrics (Bornmann, 2014).

Altmetrics typically accumulate quickly, primarily immediately after the article is published online (Mohammadi and Thelwall, 2014; Haustein et al., 2014a; Priem et al., 2011). Altmetrics are currently being investigated for a variety of applications, ranging from early measurement of article impact to potential indicators of societal relevance of research (Tahamtan & Bornmann, 2020; Thelwall, 2021; Bornmann, 2014; Garcovich & Adobes Martin, 2020). Altmetric data is also used to determine whether research has a broader impact on policy, such as on clinical practices, technical applications, education, health policy, and other areas (Haustein et al., 2014a; Haustein et al., 2014b). Altmetrics are gaining popularity and credibility in the research community, and they are also being investigated for research evaluation purposes. Altmetrics are currently being investigated for funding, recruitment, tenure, and promotion decisions (Lin, 2012; Thelwall et al., 2015).

2. Background and Objectives

Despite the growing recognition of altmetrics as a complementary tool to the traditional scientometric approach, there were limited studies that tried to analyze the association between traditional citation-based indicators and social media mentions within a specific context (Alotaibi et al., 2016; Mueller et al., 2023; Ortega, 2015; Oliveira et al., 2021; Zhang & Earp, 2020; Biranvand & Cheraghi, 2022). Although studies like the ones by Thelwall (2017, 2018) analysed the relationship between citation counts and Mendeley readers for different fields, at the level of actors of science and technology like individual scholars, institutions, etc., little explorations are found. Also, most of the studies explored the relationship between raw indicators (directly provided by databases). Studies that cover the relationship between raw indicators and derived indicators have not been found. The first gap is partially addressed, and the second gap is more profoundly addressed in this work by attempting to do an institutional-level exploration of the relationship between traditional indicators and altmetric indicators (that includes raw as well as derived indicators).

Thus, the primary objective of this study is to investigate the relationship between:

(i) Raw altmetric indicators and raw traditional scientometric indicators

(ii) Derived altmetric indicators and raw traditional indicators

(iii) Raw altmetric indicators and derived traditional indicators

(iv) Derived altmetric indicators and derived traditional indicators

Such an exploration might reinforce the usability of altmetrics to be used in raw form as well as via derived indicators, which will, in turn, shed more light on parallelism between altmetrics and traditional scientometrics.

3. Data & Methodology

3.1. Data

The main purpose of this study is to investigate the relationship between Social Media Metrics and Academic productivity metrics at the institutional level. The dataset has thus been collected from two different sources - (i) Web of Science (WoS) for bibliometrics data, and (ii) Altmetric.com for altmetric data. First, a set of institutions were selected from the WoS database. The institutions selected were Indian institutions, which had at least **1000** publications within a given time period. The time period selected for the study was **2011** to **2020**. A total of **135** institutions were selected for the study. The data was then downloaded institution-wise from the WoS database. This data was composed of 67 fields including title (TI), abstract (AB), unique IDs (UT), citations (Z9), DOIs (DI), etc.

The next step was to obtain social media data for these WoS publication records. Altmetric.com., an altmetric aggregator, was used to collect information about the social media activities for these retrieved publication records. In order to obtain altmetric data from Altmetric.com, a DOI lookup was performed for all the DOIs in the WoS data. Data was downloaded in August 2023. Altmetric data had 46 fields including DOI, Title, Twitter mentions, Facebook mentions, News mentions, Altmetric Attention Score (AAS), OA Status, Subjects (FoR), Publication Date, URI, etc. Out of this, we mainly used data for Twitter, Facebook, Mendeley, News, and Blog platforms. The field of Altmetric Attention Score (AAS) was also referred to.

3.2. Methodology

The schematic diagram of the study is given in Fig. 3.1. The exploratory analysis is performed by (i) collecting unprocessed output metrics from databases like WoS and altmetric.com and (ii) computing the derived metrics like *h*-index (Hirsch, 2005, *g*-index (Egghe, 2006), ψ-index (psi) (Lathabai, 2020), *x*-index (Lathabai *et al*., 2021), x_d -index (Nandy *et al*., 2023) using citations as well as various social media mentions like Twitter, Facebook, news, blog, etc. Derived indicators (like *h*, *g*, ψ, *x* and x_d) require additional computation. The indices can be defined as - .

ψ **-index:** An actor is said to have a ψ-index value of if is the highest rank/position such that the citations received by top ψ cited papers average at least to ψ +1/ 2.

x **-index:** An actor is supposed to have an x-index value of x if it has published papers in at least x thematic areas with thematic strengths of at least x. Here, thematic areas refer to finer thematic areas like author-provided keywords.

x_d-index: An actor is supposed to have an **x_d**-index value of if it has published papers in at least subject categories with thematic strengths of at least **x_d**. Here, subject categories refer to the broad subject categories provide by the database.

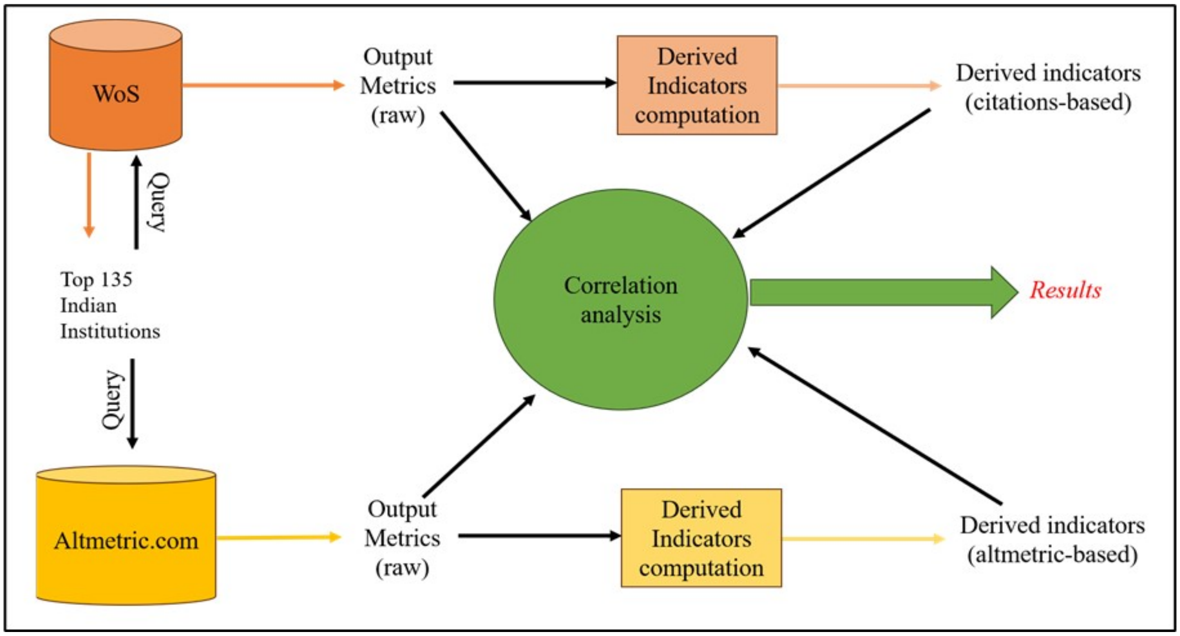

Figure 3.1. Schematic diagram

Analysis of Spearman's rank correlation between (i) raw metrics (productivity and impact indicators like total publications and total citations) and raw altmetrics (like AAS, Twitter mentions, blog mentions, new mentions, Mendeley reads, etc), (ii) raw metrics and derived altmetric indicators (h, g, ψ, x and x_d from altmetrics), (iii) derived indicators (citations-based) and raw altmetric indicators and (iv) derived indicators (citations-based) and derived altmetric indicators. Computer programs were written in Python for the computation of derived metrics as well as for derived altmetrics.

For the first step, for each institution, we have filtered out datasets obtained from both databases (WoS and altmetric.com) to include only common DOIs. Then, for the common dataset, we extracted raw indicators from both databases. Derived indicators like h, g, and were computed using publications and citations data as specified by Hirsch (2005), Egghe (2006) and Lathabai (2020) respectively. For computation of x and indices, we have built a bi-partite network with edges from UT (unique IDs) nodes to thematic areas (keywords for x computation and WoS category for computation) nodes, as directed by Lathabai et al. (2021) and Nandy et al. (2023). The network was then converted into a weighted network using the 'injection process', as explained by Lathabai (2017). The injection process uses the scores, as mentioned above, as edge weights for the links between the two types of nodes. Further, we computed weighted indegrees of each thematic area (keywords or subject categories), which gives the thematic strengths of each thematic area. Finally, the x and x_d indices can be computed from ranked thematic strengths in h-like fashion.

For instance, while calculating the x_d-index (where the network is formed between publications and WoS subject categories), the value of x_d for an institution, i is calculated using:

$$x_d = \begin{cases} r, & if\ CRR = \frac{citation\ at\ position\ r}{r} = 1 \\ r-1, & if\ CRR = \frac{citation\ at\ position\ r}{r} < 1 \end{cases} \qquad \text{Eq. 3.1.}$$

Where the position r is determined as the rank of the category in the ordered list.

4. Results and Discussions

This study analyses the relationship between traditional citation-based metrics and altmetric indicators for 135 Indian institutions, each with at least 1,000 publications between 2011 and 2020. We collected raw indicators for each publication (for each institution) from which raw indicators for institutions is obtained. We also computed all the derived indicators accordingly. The Spearman's correlation analysis results are discussed next.

4.1. Raw indicators vs raw altmetric indicators

Correlation analysis (Fig. 4.1) revealed varying degrees of association between raw indicators and raw altmetric indicators. Among these, Mendeley reads showed the strongest positive correlations (greater than 0.9) with raw indicators, suggesting that Mendeley reads could serve as a reliable early indicator of scholarly impact in the case of institutions, too. Other altmetric indicators such as the Altmetric Attention Score (AAS), Twitter mentions, and news mentions exhibited moderately strong to strong positive correlations (ranging from 0.73 to 0.81) with raw indicators suggesting that these platforms might capture different dimensions of research dissemination or audience engagement that are not directly tied to traditional academic impact. As Mendeley and AAS are found to be exhibiting stronger correlations with raw indicators, our analysis with derived indicators is reported on these only.

	AAS	News	Blog	Twitter	Facebook	Mendeley
TP	0.81	0.75	0.79	0.77	0.79	**0.92**
TC	0.79	0.73	0.76	0.74	0.77	**0.93**

Figure 4.1. Correlation between raw indicators and raw altmetric indicators as heatmap

4.2. Raw indicators vs derived altmetric indicators

From Figure 4.2, among the derived indicators in the case of *x*-index derived out of Mendeley reads and x_d The index derived out of AAS exhibits the strongest correlations with total citations. Thus, the better correlations of altmetric versions of recently introduced *x* and x_d indices may hint at their better predictive power than *h*-type indicators built on altmetric data. It is to be noted that fine-level thematic mapping (x_d-index) brought the best out of Mendeley reads, while coarse-thematic mapping (-index) suited AAS well. This may indicate Mendeley reads' ability to be used for fine-thematic analysis, while AAS may be more suitable for coarse-level or broad-level assessment. ψ-index derived from Mendeley reads can also be a good potential candidate for predicting raw citations. Better resolving power of ψ-index over indices like *h* and *g* (Lathabai & Prabhakaran, 2023) can be a reason for this.

4.3. Derived citation-based indicators vs raw altmetric indicators

From Figure 4.3, Mendeley reads outperform AAS as raw altmetric indicators to have a better correlation with derived citation-based indicators. Thus, institutions having more Mendeley reads can be expected to have high fine-level expertise (reflected by citation-based *x*-index), high overall scholarly productivity and impact (reflected by citation-based *h*, *g*, ψ and indices).

4.4. Derived citation-based indicators vs derived altmetric indicators

From Figure 4.4, the *x*-index computed out of Mendeley reads is found to correlate highly with citation-based *h, g,* ψ and *x*

	AAS_x	AAS_xd	AAS_h	AAS_g	AAS_psi	Mendeley_x	Mendeley_xd	Mendeley_h	Mendeley_g	Mendeley_psi
TP	0.8	**0.9**	0.76	0.7	0.71	**0.88**	0.68	0.83	0.8	0.83
TC	0.78	**0.86**	0.74	0.69	0.7	**0.91**	0.67	0.85	0.84	**0.86**

Figure 4.2. Correlation between raw indicators and derived altmetric indicators as a heatmap

	AAS	Mendeley
Cit_x	0.72	**0.91**
Cit_xd	0.58	0.75
Cit_h	0.69	**0.9**
Cit_g	0.76	**0.88**
Cit_psi	0.76	**0.89**

Figure 4.3. Correlation between derived citation-based indicators and raw altmetric indicators as a heatmap

indices. Also, x_d-index computed out of Mendeley is found to correlate highly with citations-based x_d-index. Mendeley -index is also found to be capable of predicting citations-based ψ-indicator Thus, all these points towards the more significant potential of Mendeley reads as a source to derive many useful derived altmetric indicators than AAS (or any other altmetric sources for that matter).

	AAS_x	AAS_xd	AAS_h	AAS_g	AAS_psi	Mendeley_x	Mendeley_xd	Mendeley_h	Mendeley_g	Mendeley_psi
Cit_x	0.74	0.84	0.68	0.62	0.63	**0.92**	0.65	0.83	0.82	0.84
Cit_xd	0.55	0.81	0.54	0.53	0.53	0.74	**0.95**	0.7	0.72	0.73
Cit_h	0.69	0.81	0.64	0.58	0.59	**0.9**	0.67	0.85	0.82	0.84
Cit_g	0.76	0.79	0.72	0.69	0.7	**0.86**	0.62	0.82	0.84	0.85
Cit_psi	0.76	0.81	0.72	0.68	0.69	**0.88**	0.64	0.83	0.85	**0.86**

Figure 4.4. Correlation between derived citation-based indicators and derived altmetric indicators as a heatmap

5. Conclusion

Thus, analyses (given in sections 4.1 to 4.4) are summarised as:

1. Mendeley reads (raw altmetric) correlate highly with raw citations and derived citation indicators like *Cit_x, Cit_h, Cit_g* and *Cit_ψ* (from analyses given in 4.1 and 4.3).

2. Derived indicators from Mendeley reads like (*a*) Mendeley_*x* correlates highly with total citations (raw indicator) and derived indicators like *Cit_h, Cit_g, Cit_ψ* and *Cit_x* (see 4.2 and 4.4), (b) Mendeley_x_d correlates highly with *Cit_*x_d (see 4.4), (c) Mendeley_*psi* correlates highly with total citations (see 4.2) and *Cit_ψ* (see 4.4).

3. AAS_x_d i.e., x_d-index derived from AAS highly correlates with total citations.

From our analyses, the overall impression is that:

1. Mendeley reads are a better raw altmetric indicator than AAS for institutional analysis. Thus, Mendeley reads are recommended as a raw altmetric indicator for early impact assessment at the institutional level.

2. Mendeley reads is also a better source than AAS to derive useful indicators that may be used to predict future raw citations as well as derived citation-based indicators for institutions. Among the derived indicators that can be computed out of Mendeley, *x,* ψ and x_d and (in the specified order) are most useful.

3. x_d indicator derived out of AAS is also a potential predictor of total citations, but not as good as *x* calculated from of Mendeley. Thus, Mendeley read is a source that can be used to derive expertise indices at the fine-thematic and broad-thematic levels, while AAS is useful for deriving an index that is capable of reflecting broad-level expertise.

Thus, we observe that some of the altmetric indicators (in their raw form) and their derived indicators can be used similarly to their traditional counterparts. However, there is no strong evidence to indicate that all the raw and derived altmetric indicators provide results in good congruence with traditional indicators. Therefore, we do not claim that these results are conclusive. However, the results are no less than suggestive of Mendeley's ability to read as a raw indicator as well as a source of derived indicators. This calls upon the need for in-depth further research that may cover more institutions from India, from other countries or regions, etc., and many more indicators (not used in this study) that may shed more light on the usability of altmetric indicators as early impact assessment indicators and forerunner of citations. Such studies may provide more concrete, conclusive evidence. Our current study may be viewed as a stepping stone in that direction.

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