Evaluating journals' yearly impact with altmetric indicators*

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Abstract

Purpose: Applying SSCI journals of library and information science (LIS) as the research sample, we explore the feasibility of measuring academic journals' yearly social impact by using altmetric indicators.

Design/methodology/approach: Using a sample of 66 SSCI journals in LIS published in 2013, statistics regarding journal mentions in social media and other online tools were retrieved from Altmetric.com and meanwhile citation data was also collected from JCR and Scopus. Based on the method of principal component analysis, data was analyzed for associations between the altmetric and traditional metrics to demonstrate the effect of altmetric indicators on measuring academic journals' yearly impact.

Findings: The Spearman's rank correlation test results show that altmetric indicators and traditional citation counts were significantly correlated, indicating that altmetrics can be used to measure a journal's yearly social impact.

Research limitations: The time frame of data collected from Altmetric.com may not be consistent with that of JCR and Scopus citation data.

Practical implications: A new method is provided based on altmetrics for evaluating the social impact of academic journals, which can be applied to design new indicators of short-term journal impact.

Originality value: In this paper, we have established a method for evaluating the social impact of academic journals based on altmetric indictors. Altmetrics can be complementary to traditional citation metrics in assessing a journal's impact within a year or even in a shorter period of time.

Keywords Altmetrics; Journal evaluation; Informetrics; Bibliometrics; Principal component analysis (PCA)

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1 Introduction

The emergence of social media tools such as Twitter and Facebook has made it easier for researchers to engage with the public and disseminate their research more widely than ever. When an increasing number of scholars are using social media tools in their professional communication in the Web2.0 era, it remains a challenge to measure the impact of research in social media. Alternative metrics (altmetrics) provides a new opportunity for the study of informetrics in the Web2.0 era.

Torres-Salinas et al.[2] defined altmetrics as the "creation and study of new indicators for the analysis of academic activity based on Web2.0" and altmetric metrics such as mentions in blogs may be a valid measure of the use and the impact of scientific publications. Qiu & Yu[3,4] pointed out that altmetric is an aggregator of online attention to scholarly papers, which provides an intuitive understanding of both social and academic influence of research findings. Altmetrics has been recently applied in scientific contexts. A large number of publishers such as PLoS ONE have adopted altmetric measures to assess the online impact of scientific literature. In June, 2014, the American National Information Standards Organization developed a draft altmetrics standard[5].

The study of altmetrics, however, is still in its initial stage. On the one hand, researchers are investigating potential use of altmetrics as a source of impact assessment. You et al.[6] used the method of principal component analysis to build a model to measure the impact of research articles with the data from the Mendeley platform. Their study suggested that the research influence measured by the social media tools is related to traditional citation-based impact. Hammarfelt[7] analyzed the altmetric coverage and influence of journals and books in humanities published by the Swedish universities in 2012. He pointed out that altmetrics could evolve into a valuable tool for evaluating research in humanities. Zahedi et al.[8] collected randomly 20,000 publications from the Web of Science, analyzed their presence and distribution in the social media, and found a moderate Spearman correlation (r = 0.49) between Mendeley readership counts and citation indicators. Alhoori et al.[9] studied altmetrics based on the country-level impact and concluded that altmetrics can be used to evaluate the impact of research activities of all countries. They found significant correlation between country-level altmetrics and several traditional bibliometric measures.

On the other hand, altmetric indicators' effect on impact assessment has been found to be rather limited. Costas et al.[10] reported positive but relatively weak correlation between altmetric indicators and citations. Therefore, they considered altmetric indicators only as a supplementary tool of citation analysis. Ortega[11] studied the correlation between altmetric indicators and traditional citation counts

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at the author level and they also found a very weak correlation between altmetrics and citations. Due to their limitations, altmetric indicators have not yet been as widely accepted as traditional citation metrics[12]. As Ortega[11] has pointed out, altmetrics cannot be a substitute of citation counts.

The existing research into altmetrics focuses more on the evaluation of social impact at the article level rather than at the journal level[13]. To the scientometrics community, however, it is important to assess academic journals' impact with bibliometric measures. One limitation of using traditional bibliometric indicators to measure journal impact is that accumulation of citations takes time and therefore it is challenging to assess a journal's impact in an immediate way. Compared with traditional bibliometrics, altmetrics has the potential to provide information about a journal's social impact in a timely manner since mentions of articles can be tracked in social media and online tools even before the articles are formally published. Whether the altmetrics can be used to measure a journal's social impact in a shorter period of time has been an issue worthy of great attention. This paper attempts to explore the feasibility of evaluating academic journals' yearly impact by using data collected from Altmetric.com. To this end, the method of principal component analysis is used to explore the relationship between online readership and traditional citation counts.

2 Data collection and selection of altmetric indicators

2.1 Data collection

Altmetric.com① is committed to developing altmetric tools and providing related services. It tracks the attention that scholarly articles and datasets receive online by pulling in data from 3 main sources in real-time: 1) social media like Twitter, Google+, Pinterest and blogs, 2) traditional media such as news outputs and government documents, and 3) online reference managers like Mendeley and CiteULike. It indicates the amount of attention each research output receives with Altmetric score, which is calculated by assigning weights to each source tracked by Altmetric.com.

Using a sample of 66 journals in library and information science (LIS) indexed in the Social Sciences Citation Index (SSCI), we collected data from 13 sources for mentions of these journals in 2014 and the annual Altmetric score for the related articles from Altmetric.com (download time: December 14, 2014). Table 1 shows partial data of the sample. Specific steps of data collection are summarized as follows:

① http://www.altmetric.com/

- Step 1: Collect the ISSNs of SSCI journals in the field of LIS from Journal Citation Reports (JCR)[2];
- Step 2: Search for journals based on the ISSNs on Altmetric.com[3], and collect data within one-year period. Raw data mainly includes the title of article, digital object identifier (DOI), source journals, Altmetric score and the number of mentions in each source. After standardizing all journal titles, we import the data into MySQL database for statistical analysis. For each journal, we calculate the total article mentions in the 13 data sources traced by Altmetric.com, the total Altmetric score, and the total number of articles published in 2014;
- Step 3: Find the latest JCR impact factor, JCR total cites and JCR immediacy index[4] of the 66 SSCI journals;
- Step 4: Download citation data published by Scopus, such as source normalized impact per paper (SNIP)[5], SCImago journal rank (SJR)[6], Scopus impact factor[7] and h-index[8].

Table 1 Partial data about SSCI journals in LIS field

Journal title	Article number	Total score	Articles in 2014	JCR TC	JCR IF	JCR II	SNIP	SJR	Scopus IF	H-index
JAMIA	374	2141	230	5937	3.932	1.251	2.46	2.594	4.53	96
JASIST	130	926	214	5125	2.230	0.290	2.15	1.745	3.30	83
JCMC	131	1563	57	2368	2.019	0.429	1.67	1.958	3.12	64
Scientometrics	201	800	362	5129	2.274	0.329	1.54	1.412	2.74	65
HILJ	74	247	39	429	0.932	0.636	1.07	0.767	1.25	24
JMLA	116	448	73	716	0.979	0.119	1.11	0.721	1.05	37
TP	53	158	95	981	1.128	0.071	1.41	0.627	1.60	40
SSCR	82	338	53	701	1.542	0.176	1.62	1.481	1.85	38
JOI	42	176	90	1152	3.580	0.600	2.02	2.541	4.46	32
T&I	31	93	56	263	0.705	0.184	1.31	0.412	1.35	26

Note: Full journal titles are listed in Appendix I. Article number: The total number of journal articles mentioned by Altmetric.com; Total score: Total Altmetric score within one-year period; JCR TC: JCR total cites; JCR IF: JCR impact factor; JCR II: JCR immediacy index; SNIP: Source normalized impact per paper; SJR: SCImago journal rank; Scopus IF: Scopus impact factor.

2.2 Selection of altmetric indicators

The data sources from which we collected data were quite different in medium nature and the number of users. We found mentions in social media and other online

[2] http://www.webofknowledge.com/JCR/JCR
[3] http://www.altmetric.com/login.php. Users need to apply for access to Altmetric.com.
[4] http://www.webofknowledge.com/JCR/JCR
[5] http://www.journalindicators.com/
[6] http://www.scimagojr.com/
[7] http://www.scimagojr.com/
[8] http://www.scimagojr.com/

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tools were not evenly distributed (Table 2). In addition, the altmetric indicators are related with one another as a person may forward a microblog post, and meanwhile he or she may include that article in the online reference managers. Considering the uneven distribution of data, we analyzed the correlation among 13 altmetric indicators using Spearman's rank correlation test. Table 3 displays the correlation results among the altmetric indicators.

Table 2 Distribution of mentions of journals in social media and online tools

Source	*N*	Min. value	Max. value	Mean	Std. deviation
Reddit threads	66	0	8	0.23	1.072
Bloggers	66	0	81	7.88	15.868
Tweeters	66	0	3199	232.34	501.451
Google+ authors	66	0	38	2.77	6.269
F1000 reviews	66	0	1	0.03	0.174
Pinterest posts	66	0	1	0.02	0.124
News outlets	66	0	58	3.66	11.481
Facebook walls	66	0	121	8.65	18.426
Sina Weibo users	66	0	1	0.05	0.211
Peer review sites	66	0	11	0.35	1.634
Policy documents	66	0	3	0.18	0.527
Mendeley readers	66	0	17294	930.00	2290.052
CiteULike readers	66	0	306	29.91	61.683

3 Journal impact evaluation with PCA

3.1 Principal component analysis

This paper uses principal component analysis (PCA) to evaluate the influence of academic journals, analyzing the correlation between comprehensive principal component scores and traditional citation indicators to avoid subjective evaluation and eliminate the impact of correlation between data.

Principal component analysis, as a multivariate statistical method, deals with high dimensional data by reducing it to a smaller dimension. It aims at finding a few linear combinations of variables, called principal components, to explain as much of the variance in the data as possible[14]. These new variables, the identified principal components, are low dimensional, unrelated, and cannot be directly measured. One of the advantages of using PCA for evaluating journals is that the weight of indicators is assigned more objectively[15–17]. Song et al.[18] analyzed major dimensions of scientific evaluation with PCA using article-level metric data sample of 1,390 articles on physics, chemistry, sociology, and immunology from PLoS ONE website.

PCA consists of the following steps[15,19]:

Table 3 Spearman's rank correlation coefficient among altmetric indicators

	Reddit	Bloggers	Tweeters	Google+	F1000	Pinterest	News	Facebook	Weibo	Peer	Policy	Mendeley	CiteULike
Reddit	1												
Bloggers	0.468**	1											
Tweeters	0.488**	0.763**	1										
Google+	0.465**	0.738**	0.747**	1									
F1000	0.563**	0.296*	0.285*	0.299*	1								
Pinterest	0.411**	0.211	0.213	0.224	0.702**	1							
News	0.371**	0.259*	0.517**	0.475**	0.306*	0.230	1						
Facebook	0.473**	0.623**	0.791**	0.740**	0.287*	0.215	0.460**	1					
Weibo	0.202	0.178	0.160	0.197	–0.039	–0.027	0.017	0.246*	1				
Peer	0.518**	0.388**	0.407**	0.349**	0.293*	0.447**	0.264*	0.382**	–0.063	1			
Policy	0.479**	0.410**	0.455**	0.429**	0.178	0.300*	0.229	0.440**	0.117	0.561**	1		
Mendeley	0.447**	0.580**	0.715**	0.642**	0.285*	0.207	0.636**	0.713**	0.033	0.291*	0.302*	1	
CiteULike	0.490**	0.628**	0.693**	0.740**	0.275*	0.214	0.579**	0.696**	0.092	0.322**	0.344**	0.863**	1

Note: Reddit: Reddit threads; Google+: Google+ authors; F1000: F1000 reviews; Pinterest: Pinterest posts; News: News outlets; Facebook: Facebook walls; Weibo: Sina Weibo users; Peer: Peer review sites; Policy: Policy documents; Mendeley: Mendeley readers; CiteULike: CiteULike readers.
** Statistically significant at the 99% confidence level (double sided).
*Statistically significant at the 95% confidence level (double sided).

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- Step 1: Standardization of raw data. The raw data (i.e. matrix X) consists of n sample and p dimensional vector, and its element x_{ij} conducts standard transformation to obtain the standardization matrix Z = $[z_{ij}]_{n\times p}$, which is calculated with Eq. (1).

$$z_{ij} = \frac{x_{ij} - \overline{x_j}}{s_j}, i = 1,2,\ldots,n; j = 1,2,\ldots,p \tag{1}$$

In Eq. (1), $\overline{x_j}$ and s_j indicate the mean and standard deviation of j column data in matrix X, respectively. They are calculated using Eqs. (2) and (3).

$$\overline{x_j} = \frac{\sum_{i=1}^{n} x_{ij}}{n} \tag{2}$$

$$s_j^2 = \frac{\sum_{i=1}^{n} (x_{ij} - \overline{x_j})^2}{n-1} \tag{3}$$

- Step 2: Calculation of the covariance matrix S of the normalized matrix Z with Eq. (4).

$$S = [s_{ij}]_{p\times p} \tag{4}$$

In Eq. (4), the covariance s_{ij} is computed with Eq. (5).

$$s_{ij} = \frac{1}{n-1}\sum_{k=1}^{n} (z_{ki} - \overline{z_i})(z_{kj} - \overline{z_j}),\ i,j = 1,2,\ldots,p \tag{5}$$

In Eq. (5), $\overline{z_j}$ indicates the mean of j column data in matrix Z and is calculated by using Eq. (6).

$$\overline{z_j} = \frac{\sum_{k=1}^{n} x_{kj}}{n},\ j = 1,2,\ldots,p \tag{6}$$

- Step 3: Computation of eigenvalue λ_i of matrix S and corresponding unit orthogonal eigenvectors a_i. For the characteristic equation $|S - \lambda I_p| = 0$ of matrix S, we find p characteristic roots. The eigenvalues of matrix S are calculated and represented as $\lambda_1 \sim \lambda_p$. The first m larger feature values $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_m$ are the variances of m principal components, and λ_i corresponds to the unit eigenvector a_i, which is also the factor between principal component F_i and the original p dimensional vector X_j.
- Step 4: Determination of the number of principal components. The variance contribution rate of each principal component is calculated with Eq. (7):

$$g(i) = \lambda_i / \sum_{k=1}^{p} \lambda_k (i = 1,2,\ldots,m) \tag{7}$$

The accumulated variance contribution rate of m principal components is computed with Eq. (8):

$$G(m) = \sum_{i=1}^{m} \lambda_i \Big/ \sum_{k=1}^{p} \lambda_k \tag{8}$$

Choose the smallest m value so that $G(m)$ is equal or greater than 80%, which means sufficient information reflects the original variables.

- Step 5: Computation of component matrix. Principal component load $l(F_i, X_j)$ reflects the correlation between the principal component F_i and the original variable X_j, and it is computed with Eq. (9).

$$l(F_i, X_j) = \sqrt{\lambda_i}\, a_i \,(i = 1,2,\ldots,m; j = 1,2,\ldots,p) \tag{9}$$

In Eq. (9), a_i indicates λ_i corresponding unit orthogonal eigenvectors.

- Step 6: Calculation of the principal component score with Eq. (10).

$$F_i = \sum_{k=1}^{p} a_{ki} Z_{\mathrm{k}} \,(i = 1,2,\ldots,m) \tag{10}$$

In Eq. (10), a_{ki} (k = 1,2,…,p) indicates the k dimensional elements of vectors a_i, Z_k (k = 1,2,…,p) indicates k column vectors of the normalized matrix Z.

- Step 7: Calculation of comprehensive evaluation (F) of m principal components with Eq. (11).

$$F = \sum_{i=1}^{m} F_i \lambda_i \Big/ \sum_{k=1}^{m} \lambda_k \tag{11}$$

3.2 Suitability of the data for PCA

Kaiser-Mayer-Olkin(KMO)-Bartlett was conducted to make sure the data was suitable for principal components analysis. KMO value ranges between 0 and 1 and the value close to 1 means there are more common factors for a group of variables, meeting the requirement for PCA analysis. The KMO value for our data sample was 0.768, which was close to 1. PCA analysis requires the Bartlett test of sphericity is statistically significant. The probability associated with the Bartlett test for our data sample was less than 0.05. KMO-Bartlett test results indicate we satisfied the basic requirement for PCA analysis.

3.3 Data processing

Data processing was conducted by SPSS statistics software[19]. First, the data in Table 1 was imported into the SPSS 19.0 and standardized. For example: Reddit threads index corresponds to the standardized index Zscore: Reddit threads. Table 4 shows each journal's Zscore for each indicator.

Second, we computed eigenvalues, feature vector and total variance explained and the result was displayed in Table 5. It is observed that the first 3 principal

Table 4 Partial data of journals' Zcore for each data source

Journal title	Zscore: Reddit	Zscore: Bloggers	Zscore: Tweeters	Zscore: Google+	Zscore: F1000	Zscore: Pinterest	Zscore: News	Zscore: Facebook	Zscore: Weibo	Zscore: Peer	Zscore: Policy	Zscore: Mendeley	Zscore: CiteULike
JAMIA	2.5834	3.34779	5.91615	5.61949	5.5692	7.9382	4.29727	6.09761	–0.21827	4.06760	1.54679	2.26327	4.4760
JASIST	0.7176	4.60818	2.44423	1.79136	–0.1770	–0.1240	0.98756	1.86443	–0.21827	–0.21656	1.54679	1.49953	3.6654
JCMC	7.2479	2.59155	3.20003	3.86493	–0.1770	–0.1240	4.73276	3.11268	4.51096	–0.21656	–0.35020	7.14569	3.9734
Sciento-metrics	0.7176	3.03269	1.11608	1.47235	5.5692	–0.1240	0.46497	1.32172	–0.21827	–0.21656	–0.35020	0.56855	0.7472
HILJ	0.7176	–0.24430	0.38421	–0.12270	–0.1770	–0.1240	–0.23181	–0.08934	–0.21827	6.51569	1.54679	–0.11700	0.7148
JMLA	0.7176	1.52022	0.74117	0.03681	–0.1770	–0.1240	–0.31891	2.19006	–0.21827	1.00748	3.44379	0.27292	1.5092
TP	–0.2150	–0.43340	–0.24796	–0.44170	–0.1770	–0.1240	0.55207	–0.19788	–0.21827	–0.21656	–0.35020	–0.11660	–0.3070
SSCR	–0.2150	0.07078	0.37623	0.03681	–0.1770	–0.1240	–0.23181	–0.03507	–0.21827	–0.21656	1.54679	0.11091	0.1150
JOI	–0.2150	0.32285	0.18878	1.47235	–0.1770	–0.1240	0.29077	–0.14361	–0.21827	–0.21656	–0.35020	–0.10130	0.5851
T&I	–0.2150	–0.49640	–0.29183	–0.28220	–0.1770	–0.1240	–0.05762	–0.14361	–0.21827	–0.21656	–0.35020	–0.19080	–0.4520

Note: Reddit: Reddit threads; Google+: Google+ authors; F1000: F1000 reviews; Pinterest: Pinterest posts; News: News outlets; Facebook: Facebook walls; Weibo: Sina Weibo users; Peer: Peer review sites; Policy: Policy documents; Mendeley: Mendeley readers; CiteULike: CiteULike readers.

components with initial eigenvalues greater than 1 explain roughly 80% of the total variability in the standardized data. As a result, selection of the first 3 principal components is a reasonable way to reduce data dimensions.

Table 5 Total variance explained

Component	Initial eigenvalues			Extraction sums of squared loading		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	7.655	58.882	58.882	7.655	58.882	58.882
2	1.794	13.800	72.682	1.794	13.800	72.682
3	1.048	8.063	80.745	1.048	8.063	80.745
4	0.727	5.594	86.339			
5	0.604	4.648	90.987			
6	0.410	3.157	94.145			
7	0.290	2.234	96.379			
8	0.253	1.946	98.325			
9	0.098	0.756	99.082			
10	0.058	0.445	99.526			
11	0.029	0.223	99.750			
12	0.023	0.173	99.923			
13	0.010	0.077	100.000			

Third, we calculated comprehensive principal component scores. Component matrix refers to factor loadings matrix of principal components with each factor loading value indicating the relationship between each variable and principal components. Table 6 shows the component matrix.

In Table 6, the first principal component includes the variables of Reddit threads, bloggers, tweeters, Google+ authors, F1000 reviews, Pinterest posts, news outlets, Facebook walls, Mendeley readers and CiteULike readers. We can substitute one component variable for this combination of variables in further analyses. The variables Sina Weibo users and peer review sites are included in the second principal component. It can substitute this combination of variables in further analyses. The third principal component includes policy documents, indicating that it reflects the basic information of the indicator. In short, the extracted 3 principal components can basically reflect the information of all the indicators, and can be used as new variables to replace the original 13 variables.

Finally, using each principal component score ($F1$, $F2$, $F3$) computed with Eq. (10) and their weights, we calculated the comprehensive principal component score F of each journal with Eq. (11). The weight was calculated as variance contribution rate against accumulated variance contribution rate. The final results are presented in Table 7.

3.4 Correlation between altmetric indicators and citation counts

Spearman's rank correlation test was conducted to analyze the correlation between the journals' yearly comprehensive principal component score F and traditional

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Table 6 Component matrix

	Principal component		
	1	2	3
Zscore: Reddit threads	0.809	–0.480	0.004
Zscore: Bloggers	0.835	0.011	–0.012
Zscore: Tweeters	0.970	0.110	–0.002
Zscore: Google+ authors	0.945	0.012	–0.139
Zscore: F1000 reviews	0.639	0.464	–0.361
Zscore: Pinterest posts	0.706	0.508	–0.190
Zscore: News outlets	0.849	–0.157	–0.020
Zscore: Facebook walls	0.961	0.120	–0.009
Zscore: Sina Weibo users	0.305	–0.679	0.193
Zscore: Peer review sites	0.472	0.482	0.364
Zscore: Policy documents	0.328	0.254	0.830
Zscore: Mendeley readers	0.805	–0.527	–0.027
Zscore: CiteULike readers	0.919	–0.060	0.053

Table 7 Partial data of factor score, component score, and comprehensive principal component score

Journal title	FAC1	FAC2	FAC3	*F*1	*F*2	*F*3	*F*
JAMIA	6.89251	0.43520	1.49212	15.53	5.44	–1.59	12.10
JASIST	0.85305	1.72684	1.31719	5.71	–0.46	1.02	4.19
JCMC	–0.32219	7.26533	–1.08616	11.60	–8.08	–0.13	7.06
Scientometrics	2.77579	–0.15069	–1.47494	4.17	1.56	–2.57	3.05
HILJ	–0.10044	–0.62741	4.02096	1.52	2.45	3.71	1.90
JMLA	–0.26570	0.46596	3.32406	2.67	0.90	3.23	2.42
TP	–0.10144	–0.11461	–0.33096	–0.64	–0.12	–0.27	–0.51
SSCR	–0.34032	–0.00742	1.16666	0.14	0.30	1.22	0.28
JOI	0.33900	0.13349	–0.39289	0.63	–0.06	–0.50	0.40
T&I	–0.10649	–0.22881	–0.33576	–0.86	–0.01	–0.29	–0.66

Note: FAC: Factor score; *F*1: The score of the first principal component; *F*2: The score of the second principal component; *F*3: The score of the third principal component; *F*: The comprehensive principal component score.

journal evaluation indicators, and the results were summarized in Table 8. It is noted that *F* has a significant correlation with all the other indicators. This shows that the comprehensive principal component score can be used for evaluation of journals' yearly social impact, and altmetrics can be considered as a supplement to traditional bibliometric indicators.

Table 8 Spearman's rank correlation coefficient between the evaluation indicators

		JCR TC	JCR IF	JCR II	SNIP	SJR	Scopus IF	H-index
F	Correlation coefficient	0.606**	0.535**	0.535**	0.541**	0.484**	0.489**	0.529**
	Sig.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: JCR TC: JCR total cites; JCR IF: JCR impact factor; JCR II: JCR immediacy index; SNIP: Source normalized impact per paper; SJR: SCImago journal rank; Scopus IF: Scopus impact factor.
** Statistically significant at the 99% confidence level (double sided).

4 Conclusions

Using the data of Altmetric.com, we extracted related citation data of 66 SSCI journals from social media and other online media within one year's time. We calculated comprehensive principal component scores to evaluate journals' social impact based on the method of principal component analysis (PCA). As an objective method to identify patterns in data, PCA is suitable for the study of altmetrics. Spearman's rank correlation analysis shows that altmetrics correlate significantly with traditional measures and they can be used to supplement traditional bibliometric indicators in reflecting the multidimensional nature of scholarly impact in an immediate way. Hopefully, our findings will encourage more research into altmetrics as complements to traditional citation measures in assessing academic journals' yearly social impact.

While traditional bibliometrics could not address the issue of evaluation of short-term journal impact, altmetrics provides an alternative. But it should be noted that related indicators need to be further studied and improved.

Our study has several limitations. First, tools such as Altmetric.com can track a limited number of social media and part of data is not provided in a standardized format, which will affect the accuracy of statistics. In addition, the Altmetric score represents a weighted count of the amount of attention to a research output, but whether the weight is assigned in an objective way needs to be further studied.

This study tried to assess academic journals' yearly social impact, but it is still a challenging task to evaluate journals' quarterly or monthly impact, or even weekly and daily impact due to the difficulties of data collection of altmetric indicators at present. But theoretically it is possible to measure academic journals' shorter-term social impact when comprehensive data in standardized formats can be available.

This paper is confined to the discussion of evaluation of social impact of SSCI journals in the field of library and information science, and this method needs to be applied to evaluate social impact of journals in other subject areas in the future to verify its effectiveness.

Author contributions

S. S. Li (chqlee87@gmail.com) collected the data, analyzed the data, and wrote the first draft. F. Y. Ye (yye@nju.edu.cn, corresponding author) revised the manuscript and edited the final version of the paper.

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Appendix I: Abbreviations of journal titles

Journal title	Abbreviation
Journal of the American Medical Informatics	*JAMIA*
Journal of the American Society for Information Science and Technology	*JASIST*
Journal of Computer-Mediated Communication	*JCMC*
Scientometrics	*Scientometrics*
Health Information & Libraries Journal	*HILJ*
Journal of the Medical Library Association	*JMLA*
Telecommunications Policy	*TP*
Social Science Computer Review	*SSCR*
Journal of Informetrics	*JOI*
Telematics and Informatics	*T&I*